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Information Acquisition and Price Setting under Uncertainty: New Survey Evidence*

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Abstract

What makes prices sticky? While it is commonly understood that prices adjust only sluggishly to changes in economic conditions, the cause of sluggish price adjustment is underexplored empirically. In this paper, we argue that sluggish updating of information drives price stickiness. To this end, we use a panel dataset that contains information on both firm-level expectations and price adjustments and document the following facts: (1) there is a positive correlation between whether a firm updates its expectations and whether it adjusts prices; (2) firms update expectations more frequently and make less correlated forecast errors in downturns; and (3) firms adjust prices more frequently in downturns. We then extend an Ss price-setting model with second moment shocks to allow for endogenous information acquisition by the firm. The model predicts that firms acquire information more intensively during periods of high volatility, also adjusting expectations and prices more often. Countercyclical volatility, interacting with menu costs and information rigidity, is what drives our results. This implies that the flexibility of the aggregate price level is countercyclical, making monetary policy less effective in recessions.

Keywords: information acquisition; price stickiness; uncertainty/volatility
JEL classification: D84, E2, E3

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1 Introduction

Why do firms adjust prices only sluggishly in response to changes in economic conditions? While the role of expectations and information in price-setting behavior has been the central subject of existing theoretical debates (Mankiw and Reis, 2002, Mackowiak and Wiederholt, 2009, Hellwig and Venkateswaran, 2009, Alvarez et al., 2015), what makes prices sticky appears to remain an open empirical question. As price-setting behavior is dynamic in that firms take into account expected future demand and cost conditions, empirically isolating the source of sluggish price adjustment requires us to observe how firms form expectations about future demand and cost trajectory. However, expectations data at the micro level is rarely available, thus rendering any empirical investigation challenging.

This paper addresses this issue by using panel data on price-setting behavior, alongside measures of both macro and micro expectations at the firm level, allowing us to construct measures of forecast errors, forecast revisions, and price stickiness. Our empirical analysis reveals that (1) firms update expectations sluggishly; (2) firms adjust prices slowly to changes in costs; (3) firms are less likely to adjust prices when they do not update macro and/or micro expectations. Furthermore, we also find that (4) firms update expectations more frequently in recessions than in booms; and indeed (5) firms pass changes in costs/demand on to prices more frequently in recessions than in booms as well. In light of the evidence, we extend a Ss price-setting model to allow for endogenous information acquisition and second moment shocks to quantify the importance of information rigidity on price-setting behavior and the flexibility of the aggregate price level. We show that firms acquire information more frequently in periods of high volatility, and thus they change prices more frequently. In our model with second moment shocks, recessions are times when volatility is high as extensively documented in the literature.[1] What follows is that since the flexibility of the aggregate price level is countercyclical monetary policy is less effective in recessions than in booms.

The firm-level dataset we use is based on a survey called Business Outlook Survey (BOS). This survey is jointly conducted by the Ministry of Finance and the Cabinet Office of the Japanese Government and focuses on firm-level expectations for macro and micro economic conditions. The survey covers all big firms and a representative sample of medium and small-sized firms and conducted at the quarterly frequency. In addition, it includes both manufacturing firms and non-manufacturing firms and has an average response rate of 80%. We have obtained the data from 2004/Q2 to 2017/Q1 and constructed a panel dataset spanning for 52 quarters with roughly 12,000 observations per quarter. This panel dataset contains information on quan-

[1] See Bloom (2009), Kehrig (2015), Senga (2016), Bloom et al. (2018), among others.

titative sales forecasts and qualitative forecasts for macroeconomic and firm-specific demand conditions. First, the firm is asked to report *quantitative* forecasts for their sales in the current semi-year and in next semi-year.[2] Next, the firm is asked to *qualitatively* forecast the change in macroeconomic conditions and in its own demand conditions (i.e., improving, unchanged and deteriorating) for the current quarter and future quarters. Based on these information, we construct (1) a quantitative measure of forecast errors regarding sales and (2) a measure of forecast revisions (i.e., updates) about macroeconomic and firm-specific demand conditions as well as sales forecasts. The BOS dataset also contains information on changes in input and output prices at the quarterly frequency (i.e., decreasing, unchanged and increasing). We define firms that do not change the output price from the previous quarter to the current quarter as firms that have sticky price. Finally, the survey also contains information on firm size (i.e., registered capital), the industry affiliation of the firm, and the region the firm is located at.

Using BOS, we document four novel facts that are interrelated. First, there is a positive correlation between whether a firm updates its sales/macro expectations and whether it adjusts output prices. Although there are $40\% - 60\%$ firms that do not update their sales/macro expectations between two adjacent quarters, firms that do update their expectations are more likely to adjust their output prices.[3] This finding suggests that there is information rigidity, and expectations play an important role in determining price adjustment. Second, firms update the expectations more frequently and make less correlated forecast errors when the economic growth rate decreases. This finding hints that the level of information rigidity is pro-cyclical, as the probability of not updating expectations and the serial correlation of forecast errors are two important measures of information rigidity. Third, firms adjust output prices more frequently, conditional on a change in costs or demand, when the economic growth rate goes down.[4] This finding indicates that price stickiness is pro-cyclical, which echoes the finding of pro-cyclical information rigidity. Finally, firm-level volatility is counter-cyclical, as both the cross-sectional variance of sales growth rates and that of firms' sales forecst errors increase in recessions.

In the theory part, we present a Ss price setting model that features imperfect information and endogenous acquisition of information and show that this simple two-period model can rationalize the first three stylized facts documented above. Specifically, we assume that although the firm knows its demand in the first period, its demand in the second period is subject to shocks. The firm can pay a cost to acquire information about the demand in the second period. If the firm successfully acquires the demand information in the second period, it is going to update its

[2]The first semi-year ranges from Apr. to Sep., while the second semi-years spans from Oct. to Mar.

[3]Unfortunately, we cannot investigate the types of products whose prices firms are more likely to adjust, as there is no information on the products firms produce in the dataset.

[4]In addition, we find that firms adjust prices more often in both directions, when the GDP growth rate drops.

demand and thus sales expectations. Otherwise, it uses the prior belief. In the model, firms face a fixed cost of adjusting the output price from the first period to the second one. Note that the (would-be) loss of fixing the price (over two periods) increases with the size of the demand shock in the second period. Therefore, the firm changes its price, if it updates its expectations by observing that the second-period demand shocks are sufficiently large. This theoretical finding reminisces the celebrated "Ss" policy for price adjustment, as shown by Barro (1972). Moreover, it rationalizes our first stylized fact that there is an incomplete pass-through from an update in sales/demand expectations to the adjustment of output price.

Now, we discuss how the variance of demand shocks (i.e., a second moment shock) affects the firm's incentive to acquire information and adjust the price. The basic premise of the model is that the variance of firm-specific demand shocks increases, when the economic growth rate drops, which is our fourth stylized fact. For the marginal benefit of acquiring information, the second moment shock brings about two effects. First, conditional on the intensity of acquiring information, the firm is more likely to adjust its price as the realized demand shock is more likely to fall out of the "Ss" band of the price adjustment. Second, the average (would-be) loss of *not* adjusting the price is larger when the variance of demand shock is large, as the realized second-period demand is farther away from the first-period demand on average. In total, both effects increase the marginal benefit of acquiring information.[5] Therefore, the intensity of acquiring information increases, which leads to a higher probability of updating demand and sales expectations when the economic growth rate drops. This rationalizes our second stylized fact. Finally, the probably of adjusting the price is the product of the probability of observing the second-period demand condition and the probability of a realized demand shock that falls out of the "Ss" band of the price adjustment. As both the intensity of acquiring information and the variance of demand shocks increase, the probability of adjusting the price increases in downturns when volatility rises. This rationalizes our third stylized fact. In total, our simple two-period model yields predictions that are consistent with our empirical findings.

We also analyze how the mean of the firm's demand shifter (i.e., a first moment shock) affects its incentive to acquire information and to adjust the price. In our benchmark model, such a shock has no effect on information acquisition as both the benefit and the cost of adjusting the price are independent of the mean of the demand shifter.[6] In order to address this issue, we introduce a fixed cost of operation to generate the possibility of receiving negative profits in the extension of our benchmark model. Crucially, the firm is assumed to pay this fixed

[5] The cost of acquiring information is assumed to be constant over time for simplicity.

[6] Specifically, the inaction region of price adjustment centers around the mean of firm's demand shifter *symmetrically*. Moreover, the spread of the inaction region moves in the same direction and by the same degree with the mean of the demand shifter.

cost *after* the (possible) revelation of the demand shifter in the second period. As a result, there is an extra benefit of acquiring information now. That is, the firm can avoid paying this fixed cost by stopping production, if it has discovered a sufficiently low demand shifter in the second period. This extra benefit of acquiring information naturally increases in recessions, as the likelihood of drawing a demand shifter that leads to a negative realized profit increases in recessions. Therefore, firms increase the intensity of acquiring information after the first moment shock in our extended model. However, the likelihood of changing the output price either decreases or stays unchanged (after the firm has discovered its demand shifter) following the first moment shock. This is against our empirical fact that conditional on an update in demand/sales expectation, the likelihood of changing the price increases when the GDP growth rate goes down. Moreover, the overall probability of price adjustment may or may not increase after the first moment shock, against our empirical fact that the overall frequency of price adjustment goes up unambiguously when the GDP growth rate goes down.

The idea that links imperfect information to the real effects of monetary policy, dating back to Muth (1961) and Lucas (1972), has been formalized by various theories.[7] How agents process information and form expectations are central to these theories, yet it is challenging to *directly* test predictions emerging from each theory due to the lack of expectations data available for researchers. A recent empirical literature on information frictions and expectations formation began to take off, thanks to the increasing availability of expectations data from both the household side and the firm side.[8] Among others, our paper is most closely related to Coibion et al. (2018) in that they study how providing more information affects firms' decisions including the pricing decision. Our results are complementary to their work, though, as we focus on the cyclical properties of information and price rigidity and offer theoretical channels that drive cyclical fluctuations of information and price rigidity.[9]

Our results shed light on time-varying responsiveness, as pointed by Berger and Vavra (2017). Relative to Bloom et al. (2018) and Vavra (2014), Berger and Vavra (2017) argue that not only do shocks become more volatile in recessions, but also firms respond to shocks more in recessions for some reason. In this paper, we show that firms endogenously respond to second moment shocks by adjusting the intensity of acquiring information, which leads to *endogenous* firm-level uncertainty. Moreover, this endogenous response has important implications for pro-cyclical

[7]See Woodford (2001), Mankiw and Reis (2002), Mackowiak and Wiederholt (2009), Woodford (2009), Maćkowiak and Wiederholt (2015), among others.

[8]Examples include Coibion and Gorodnichenko (2012), Coibion and Gorodnichenko (2015), Tanaka et al. (2018), Bachmann and Elstner (2015), Bloom et al. (2017), Chen et al. (2018), among others.

[9]Coibion and Gorodnichenko (2015) document that information rigidity at the macro level (e.g., GDP forecasts) decreases during recessions and increases in booms. Our findings in this paper document a similar pattern but for micro-level economic variables (i.e., firm sales and demand).

price stickiness and the effect of monetary policy over business cycles.[10]

Our theoretical analysis builds on models of menu cost models such as Golosov and Lucas (2007), Nakamura and Steinsson (2008), Nakamura and Steinsson (2010), Alvarez et al. (2011), and Midrigan (2011). In particular, our model features second moment shocks as in Vavra (2014), who also shows that monetary policy can be less effective in recessions when volatility is high. Relatedly, Baley and Blanco (2019) also shows the importance of firm-level uncertainty and imperfect information in deriving monetary policy implications, common with our papers.

2 Empirical Facts

In this section, we document a set of stylized facts about firms' expectations formation and price adjustments over business cycles. We construct a panel dataset of Japanese firms to study the time-series properties of these firms' forecasts, forecast errors and price adjustments. We find that (1) the firm is more likely to adjust its (output) price when it updates its sales and/or macro expectations; (2) the degree of firm-level information rigidity measured by the serial correlation of forecast errors and the *infrequency* of forecast updating is pro-cyclical; (3) firms adjust (output) prices more frequently (and do so conditioning on a change in its costs or demand), when the economic growth rate decreases; (4) firm-level volatility is counter-cyclical. In total, we conclude that the pro-cyclical information rigidity drives pro-cyclical price rigidity.

2.1 Data

The firm-level dataset we use is based on a survey called Business Outlook Survey (BOS). This survey is jointly conducted by the Ministry of Finance and the Cabinet Office of the Japanese government and focuses on firm-level expectations for macro and micro economic conditions. The survey covers all big firms and a representative sample of small and medium-sized firms and is conducted at the quarterly frequency. In addition, it includes both manufacturing firms and non-manufacturing firms with registered capital of 10 million JPY or more. About 16,000 firms are sampled in each survey and it has an average response rate of 80%. We have obtained the data from 2004/Q2 to 2017/Q1 and constructed a panel dataset spanning for 52 quarters with roughly 12,000 observations per quarter. We label the first quarter of 2004 as quarter one and subsequently quarters two, three, four, five... The last quarter in our sample is quarter 53.

The panel dataset contains information on forecasted and realized sales and qualitative forecasts for macroeconomic and firm-specific demand conditions. First, the firm is required to

[10] A closely related empirical literature to our paper studies the cyclical nature of firm-level volatility (Bloom (2009), Vavra (2013), Bachmann and Bayer (2014), Kehrig (2015), Bachmann et al. (2017), Bloom et al. (2018)).

report *quantitative* forecasts for their sales in the current semi-year and in next semi-year (except for the survey conducted in the fourth quarter which only contains sales forecast for the current semi-year).[11] For instance, a firm in 2011/Q2 is asked to forecast its sales for the first half (2011/Q2-2011/Q3) and the second half of 2011 fiscal year (2011/Q4-2012/Q1). As firms also report realized sales in the past semi-year, we can construct the revision in sales forecast from the previous quarter to the current quarter (for the same semi-year) and the ex post forecast errors of sales.[12] Next, the firm is required to *qualitatively* forecast the change of the overall macroeconomic conditions and of its own demand conditions (i.e., improving, unchanged and deteriorating) for the current quarter and future quarters. Specifically, in quarter t, the firm is asked to forecast the change of conditions from quarter $t-1$ to quarter t, from quarter t to quarter $t+1$, and from quarter $t+1$ to quarter $t+2$. Based on these information, we construct the revision in the forecasted change of macroeconomic and firm-specific demand conditions.

The panel dataset also contains information on changes in input and output prices at the quarterly frequency. In quarter t, each firm is asked to report the prices change from quarter $t-1$ to quarter t (i.e., increasing, decreasing and unchanging) and forecasted prices change from quarter t to quarter $t+1$ and from quarter $t+1$ to quarter $t+2$. We treat the prices change from quarter $t-1$ to quarter t (reported in quarter t) as the adjustment of prices in quarter t. In addition, if the firm reports that the price is unchanged from quarter $t-1$ to quarter t, we define the price as being rigid.

In addition to information on expectations and price changes, the survey also contains information on firm size (i.e., registered capital), the industry affiliation of the firm, and the region the firm is located at.

2.2 Measurements

In this subsection, we introduce three types of variables we construct for our empirical analysis: forecast errors, forecast revisions (and updates) and price stickiness.

2.2.1 Forecast Errors

First, we define the deviation of the realized sales from the projected sales as the forecast error. Our main measure of the forecast error is the log point deviation of the realized sales from the

[11]The fiscal year in Japan spans from Apr./1 to Mar./31 next year. As a result, the first semi-year covers the periods form Apr. to Sep., while the second semi-year spans from Oct. to next Mar.

[12]The firm is also required to forecast the operating profits (at the semi-year level) and investment (at the quarterly level) in the survey.

forecasted (i.e., the projected) sales as

$$FE_t^{\log} \equiv \log\left(R_t / E_{t-1}\left(R_t\right)\right),$$

where R_t is the realized sales in semi-year t and $E_{t-1}\left(R_t\right)$ denotes the firm's prediction about sales in semi-year t formed at the beginning of semi-year t. For each semi-year, although the firm forecasts its sales *before* the beginning of each semi-year (the long-run forecast), we use the forecast made *in* the beginning of each semi-year (the medium-run forecast) as the measure to construct the forecast error due to the high response rate.[13] The forecast error in semi-year t can also be stated as $FE_{t-1,t}^{\log}$, and we use $FE_{t-1,t}^{\log}$ and $FE_t^{\log}$ interchangeably in what follows. A positive (negative)forecast error means that the firm is under-predicting (over-predicting) its sales. Alternatively, we define the percentage deviation of the forecasted sales from the realized sales as

$$FE_t^{pct} = \frac{R_t}{E_{t-1}\left(R_t\right)} - 1.$$

As constructed forecast errors contain extreme values, we trim top and bottom one percent observations of forecast errors.

Next, we construct a "residual forecast error" measure in an effort to isolate firm-level idiosyncratic components reflected in forecast errors. The components we focus on in this paper are idiosyncratic shocks that cause firms to mis-forecast their future sales, although the distribution of these components can be determined by aggregate economic conditions. In other words, we focus on micro-level volatility and information frictions. In the domestic survey, we project our two measures, $FE_t^{\log}$ and FE_t^{pct}, onto prefecture-time, industry-time and size-time fixed effects and obtain the residuals, $\hat{\epsilon}_{FE^{\log}}$ and $\hat{\epsilon}_{FE^{pct}}$.[14]

In Table 1, we present summary statistics of our four measures of forecast errors in the domestic survey.[15] While the mean of the residual forecast errors, $\hat{\epsilon}_{FE^{\log}}$ and $\hat{\epsilon}_{FE^{pct}}$, is zero by construction, the mean of FE^{log} and that of FE^{pct} are also close to zero. Since the variance of residual forecast errors is almost the same as that of forecast errors, we argue that the aggregate-level fixed effects such as region-year and industry-year fixed effects do not account for a large

[13] The response rate of the medium-term forecast (75%) is much higher than that of the long-term forecast (45%).

[14] The size indicator ranges from 1 to 7, with 7's being the indicator for the biggest firms

[15] Note that for the medium-term forecast, firms only report their projected sales in the beginning of each semi-year. Thus, the table only reports summary statistics of observations in the second and fourth quarter. Also note that as the random sample of medium and small-sized firms is redrawn every fiscal year, Many firms (25% observations) that report projected sales in Q4 do not appear in the dataset in Q2 of next year. As a result, the number of observations that have information on forecast errors is smaller than the number of observations that report medium-term forecast.

fraction of the variation of forecast errors. In addition, the mean and median of $\hat{\epsilon}_{FE^{log}}$ (and $\hat{\epsilon}_{FE^{pct}}$) are similar to those of $FE^{\log}$ (and FE^{pct}).

Table 1: Summary statistics of forecast errors

	Obs.	mean	std. dev.	median
FE^{log}	158229	-0.006	0.156	0.000
FE^{pct}	158372	0.006	0.163	0.000
$\hat{\epsilon}_{FE^{pct}}$	158229	-0.000	0.154	0.003
$\hat{\epsilon}_{FE^{log}}$	158372	-0.000	0.160	-0.006

FE^{log} is the log deviation of the realized sales from the projected sales, while FE^{pct} is the percentage deviation of the realized sales from the projected sales. $\hat{\epsilon}_{FE^{log}}$ is the residual log forecast error, which we obtain by regressing FE^{log} on a set of region-year, country-year and size-year fixed effects. Similarly, $\hat{\epsilon}_{FE^{pct}}$ is the residual percentage forecast error, which we obtain by regressing FE^{pct} on a set of industry-year, region-year and size-year fixed effects. As we utilize forecasts made in the beginning of each semi-year, errors of sales forecasts made in the second and the fourth quarters are reported in this table. Top and bottom one percent of observations are trimmed out.

2.2.2 Forecast Revisions and Updates

Now, we define the forecast revisions and updates. For the (quantitative) sales forecast, the forecast revision is defined as the log difference in the forecasts made in two consecutive quarters for the same semi-year. For the second and the fourth quarter, the forecast revision from quarter $t-1$ to quarter t is defined as

$$FR^{\log}_{t-1,t}(R_t + R_{t+1}) \equiv \log\left(E_t(R_t + R_{t+1})\right) - \log\left(E_{t-1}(R_t + R_{t+1})\right),$$

where t denotes the quarter. In other words, we use the long-run forecast made in the first or the third quarter to define the prior belief and the medium-run forecast made in the second or the fourth quarter to define the updated belief. For the first and the third quarter, the forecast revision from quarter $t-1$ to quarter t is defined as

$$FR^{\log}_{t-1,t}(R_{t-1} + R_t) \equiv \log\left(E_t(R_{t-1} + R_t)\right) - \log\left(E_{t-1}(R_{t-1} + R_t)\right).$$

Now, we use the medium-run forecast made in the fourth or the second quarter to define the prior belief and the short-run forecast made in the first or the third quarter to define the updated belief. Note that as the firm is asked to forecast the sales in the beginning of each quarter (i.e., the first month), the firm still faces uncertainty when forecasting its sales of quarter t in quarter t. We choose to define the forecast revision for sales in such a way, as the frequency of the survey (quarterly) is different from the length of the period the firm forecasts (i.e., semi-year).

Based on the revisions defined above, we create a binary variable for whether or not the firm update its sales forecast:

$$FU_{t-1,t}^{sales,strict} = 1,$$

if and only if $FR_{t-1,t}^{\log}(R_t + R_{t+1}) \neq 0$ for the second and the fourth quarter (and $FR_{t-1,t}^{\log}(R_{t-1} + R_t) \neq 0$ for the first and the third quarter) and zero otherwise. We also define a broad measure for updating the forecast as

$$FU_{t-1,t}^{sales,broad} = 1,$$

if and only if $|FR_{t-1,t}^{\log}(R_t + R_{t+1})| > 0.01$ for the second and the fourth quarter (and $|FR_{t-1,t}^{\log}(R_{t-1} + R_t)| > 0.01$ for the first and the third quarter) and zero otherwise.

For the qualitative forecast of domestic macro demand conditions (or macro demand conditions hereafter), we simply define the forecast update as

$$FU_{t-1,t}^{macro} = 1,$$

if and only if $Fore_{t-1}(macro_t) \neq Fore_t(macro_t)$, where $Fore_{t-1}(macro_t)$ is the expected change in macro demand conditions from quarter $t-1$ to quarter t made in the beginning of quarter $t-1$ (and $Fore_t(macro_t)$ is the expected change in macro demand conditions from quarter $t-1$ to quarter t made in the beginning of quarter t). Similarly, we define the forecast update for firm-specific demand conditions as

$$FU_{t-1,t}^{firm} = 1,$$

if and only if $Fore_{t-1}(firm_t) \neq Fore_t(firm_t)$ where $Fore_{t-1}(firm_t)$ is the expected change in firm-specific demand conditions from quarter $t-1$ to quarter t made in the beginning of quarter $t-1$. Note that the expected changes, $Fore_{t-1}(macro_t)$ and $Fore_{t-1}(firm_t)$, only take three values: 1 (improving), 2 (unchanging), 3 (deteriorating).

As all the qualitative forecasts are about the *change* in economic and business conditions, we can define the change of macro forecast as

$$FC_t^{macro} = 1,$$

if and only if $Fore_t(macro_t)$ equals one (i.e., improving) or three (deteriorating) and zero otherwise. Similarly, we define the change of firm-specific forecast as

$$FC_t^{firm} = 1,$$

if and only if $Fore_t(firm_t)$ equals one (i.e., improving) or three (deteriorating) and zero otherwise. In other words, both FC_t^{macro} and FC_t^{firm} are the indicator functions for a forecasted change in economic and business conditions.

In Table 2, we present summary statistics of forecast updates and forecasted change of macroeconomic and firm-specific demand conditions. The main finding is that firms do update their beliefs for future sales often even at the quarterly. For instance, 62% firms update their expected sales in two consecutive quarters. When we focus on the update in qualitative forecasts such as the forecasted change in macroeconomic conditions, this fraction drops substantially. Specifically, roughly 40% firms forecast either the macroeconomic or the firm-specific demand conditions change from the previous quarter to the current quarter.

Table 2: Summary statistics of forecast revisions and updates

	Obs.	mean	std. dev.	median
$FU_{t-1,t}^{sales,strict}$	372406	0.722	0.448	1.000
$FU_{t-1,t}^{sales,broad}$	372406	0.623	0.485	1.000
$FU_{t-1,t}^{firm}$	363168	0.305	0.460	0.000
$FU_{t-1,t}^{macro}$	393285	0.300	0.458	0.000
FC_t^{firm}	516178	0.441	0.496	0.000
FC_t^{macro}	562041	0.398	0.490	0.000

$FU_{t-1,t}^{sales,strict}$ equals one when the sales forecasts made in quarters -1and are different and zero otherwise. $FU_{t-1,t}^{sales,broad}$ equals one if the log difference between sales forecasts made in quarters $t-1$ and t is bigger than or equal to 0.01 and zero otherwise. FC_t^{firm} (and FC_t^{macro}) equals zero if the forecasted change of firm-specific (and macroeconomic) demand conditions is unchanging from quarter $t-1$ to quarter t and zero otherwise. $FU_{t-1,t}^{firm}$ (and $FU_{t-1,t}^{macro}$) equals zero if the forecasted change in firm-specific (and macroeconomic) demand conditions from quarter $t-1$ to quarter t does not change from the forecast made in quarter $t-1$ to the forecast made in quarter t and zero otherwise.

2.2.3 Price Stickiness

Finally, we define the stickiness measure of input/output price. In the beginning of quarter t, the firm reports whether it is changing the input/output price from quarter $t-1$ to quarter t:

$$price_t^{dir} = sign(price_t - price_{t-1}),$$

where $sign(price_t - price_{t-1}) = 1$ if $price_t > price_{t-1}$, 0 if $price_t = price_{t-1}$, and -1 if $price_t < price_{t-1}$. Based on this information, we define a binary variable for whether or not the firm adjusts the input/output price in quarter t:

$$price_t^{stick} = 1,$$

if and only if $price_t^{dir} = 0$.

In Table 3, we present summary statistics of price stickiness. Three observations stand out. First, the fractions of firms that change input/output prices are low. In particular, roughly a quarter of firms change their output prices every quarter. This is consistent with the observation that the inflation rate of Japan during 2004-2017 is low and stable. Second, it is clear that the fraction of firms that change input prices (36%) is higher than the fraction of firms that change output prices (26%). This is an indication that price stickiness exists, as there quite many firms that do not change their output prices even when their input prices change. This low fractions of firms that change input/output prices ($26\% - 36\%$) echo the finding that percentage of forecasted change in macro/firm-specific conditions is low (40%).

Table 3: Summary statistics of price stickiness

	Obs.	mean	std. dev.	median
$\mathit{1}\Big(\textit{output price}_t = \textit{output price}_{t-1}\Big)$	494463	0.263	0.440	0.000
$\mathit{1}\Big(\textit{input price}_t = \textit{input price}_{t-1}\Big)$	447753	0.357	0.479	0.000

$\mathit{1}\Big(\textit{output price}_t = \textit{output price}_{t-1}\Big)$ equals one when the output price is unchanged from quarters $t-1$ to t and zero otherwise. $\mathit{1}\Big(\textit{input price}_t = \textit{input price}_{t-1}\Big)$ equals one when the input price is unchanged from quarters $t-1$ to t and zero otherwise.

2.3 Fact One: A positive relationship between price adjustment and belief updating

In this subsection, we investigate how an update in the sales expectation affects the likelihood of adjusting the output price. Specifically, we regress the indicator of adjusting (output) price (i.e., $price_t^{stick}$) from quarter $t-1$ to quarter t on whether the firm updates its sales expectation from quarter $t-1$ to quarter t. We report the regression results in Table 4. In the first (and the last) three columns of the table, we use our strict (and broad) definition to define whether the firm updates its sales forecast to run the regressions. The effect of an update in sales expectation has a statistically significant and positive impact on whether the firm adjusts its output price, shown by the estimates in columns one and four. In columns two and five, we add the lagged firm size (i.e., logarithm of registered capital) and the results barely change. In columns three and four, we include the lagged firm size *and* industry-quarter and region-quarter fixed effects into the regressions. The results also barely change. In short, we find that firms are more likely to adjust (output) prices when they update sales expectations.

Although the above result hints that there is a correlation between the price adjustment and the belief adjustment, it is subject to the problem of reversed causality. Specifically, ex-

Table 4: updating in sales forecast and price adjustment

	(1)	(2)	(3)	(4)	(5)	(6)
Dep.Var:	$1\Big(output\ price_t \neq output\ price_{t-1}\Big)$					
$FU^{sales,strict}_{t-1,t}$	0.011***	0.011***	0.011***			
	(0.002)	(0.002)	(0.002)			
$FU^{sales,broad}_{t-1,t}$				0.010***	0.010***	0.010***
				(0.002)	(0.002)	(0.002)
lagged log firm size		-0.007*	-0.005		-0.007*	-0.005
		(0.004)	(0.004)		(0.004)	(0.004)
constant	0.237***	0.280***	0.268***	0.238***	0.281***	0.269***
	(0.001)	(0.022)	(0.022)	(0.001)	(0.022)	(0.022)
Industry FE	No	Yes	No	No	Yes	No
Region FE	No	Yes	No	No	Yes	No
Quarter FE	No	Yes	No	No	Yes	No
Industry-quarterly FE	Yes	No	Yes	Yes	No	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Region-quarterly FE	Yes	No	Yes	Yes	No	Yes
N	328424	328450	328424	328424	328450	328424
R^2	0.443	0.428	0.443	0.443	0.428	0.443

* 0.10 ** 0.05 *** 0.01. We regress the indicator of adjusting (output) price on whether the firm updates its sales expectation and lag firm size (i.e., log registered capital). Standard errors are clustered at the firm level.

pected sales are determined by expected output and price. Therefore, the adjustment of sales expectation (for the current and the next quarters) may be caused by the change of output price (in the current quarter). To address this issue, we replace the forecast updating measure constructed using firms' forecast about their own sales with their forecast about macroeconomic conditions, i.e., $Fore_t(macro_t)$, which is arguably not affected by a single firm's pricing decision. Moreover, as both the adjustment in the output price and the macro expectation (i.e., the expected change in macro conditions) are *qualitative* questions in the survey questionnaire, the estimation equation using them as the dependent and the independent variables yield more credible estimates.[16]

Results reported in Table 5 confirm our previous finding. In the first three columns of the table, we regress the indicator of changing the output price from quarter $t-1$ to quarter t on whether the firm expects the macroeconomic conditions to change from quarter $t-1$ to quarter t. The result shows that when the firm expects the macroeconomic conditions to change, it is 13% more likely to change its output price. This result survives, when we include the lagged firm size and/or industry-quarter and region-quarter fixed effects. As 40% firms expect the macroeconomic conditions to change across two consecutive periods on average, the contribution of an update in the macro expectation to the overall fraction of firms that change the output

[16]If we use the quantitative forecasts to define whether the firm updates the expectation in a qualitative way, which threshold we should use is somewhat unclear (it is set at 1% for the quantitative adjustment now).

price is 16.2% = 13% $*$ 40%/26% which is quantitatively important. In the last three columns, we replace the regressor of FC_t^{macro} by $FU_{t-1,t}^{macro}$. The estimation result is qualitatively the same as in the first three columns. That is, when the firm adjusts its belief for whether the macroeconomic conditions are going to change, it is more likely to adjust the output price. In short, we have established a positive correlation between an update in firm's expectations (sales or macro) and an adjustment of firm's output price. In what follows, we will study the cyclical properties of belief updating, information frictions and price adjustment.

Table 5: Updating in macro expectation and price adjustment

	(1)	(2)	(3)	(4)	(5)	(6)
Dep.Var:	$1\left(output\ price_t \neq output\ price_{t-1}\right)$					
FC_t^{macro}	0.133***	0.130***	0.129***			
	(0.002)	(0.002)	(0.002)			
$FU_{t-1,t}^{macro}$				0.036***	0.037***	0.036***
				(0.002)	(0.002)	(0.002)
lagged log firm size		-0.004	-0.003		-0.006*	-0.005
		(0.003)	(0.003)		(0.003)	(0.003)
constant	0.209***	0.224***	0.215***	0.229***	0.266***	0.259***
	(0.001)	(0.020)	(0.020)	(0.001)	(0.021)	(0.021)
Industry FE	No	Yes	No	No	Yes	No
Region FE	No	Yes	No	No	Yes	No
Quarter FE	No	Yes	No	No	Yes	No
Industry-quarterly FE	Yes	No	Yes	Yes	No	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Region-quarterly FE	Yes	No	Yes	Yes	No	Yes
N	461077	379790	379770	322579	322599	322579
R^2	0.437	0.435	0.448	0.438	0.422	0.438

* 0.10 ** 0.05 *** 0.01. We regress the indicator of adjusting (output) price on whether the firm updates its macro expectation (or expects the macroeconomic conditions to change) and lag firm size (i.e., log registered capital). Standard errors are clustered at the firm level.

2.4 Fact Two: Counter-cyclical belief updating and pro-cyclical serial correlation of forecast errors

In the literature of rational expectations models with information rigidity, there are two groups of models that have been studied. The first group of model is called the sticky information model which features *delayed* information diffusion (Mankiw and Reis (2002), Reis (2006)). The key measure for information rigidity is the fraction of agents that do not update their expectations over two consecutive periods. The second group of models include the noisy information model and the rational inattention model which all feature *partial* information diffusion (Lucas (1972), Lucas (1973), Sims (2003), Mackowiak and Wiederholt (2009)). The key measure for information rigidity in the second group of models is the serial correlation of forecast errors which negatively depends on the signal-to-noisy ratio. In this subsection, we present evidence on how economic fluctuations affect these two key measures for information rigidity.

First, we show how the fraction of firms that update sales and/or macro expectations is affected by economic fluctuations. As the update in sales forecast and the macro expectation is at the frequency of quarterly level, we use quarterly GDP growth rate. Specifically, there are two proxies we use to measure economic fluctuations: the GDP growth rate compared to the previous quarter (*grprevqr*) and the GDP growth rate compared to the same quarter of last year (*grlastqr*). We first study how the likelihood of an update in the firm's macro expectation responds to fluctuations in the quarterly GDP growth rate, as firm's macro expectations should be directly related to past economic fluctuations. In the first column of Table 6, we simply regress our (board) indicator for sales forecast revision, $FU^{macro}_{t-1,t}$, on the GDP growth rate compared to the previous quarter and include firm fixed effects. The estimated coefficient is negative and statistically significant, which suggests that a slower GDP growth rate increases the probability of adjusting firm's adjusting its macro expectation. This result is unchanged, when we include lagged firm size (the logarithm of registered capital) in column two. In column three, we add industry-quarter and region-quarter fixed effects and investigate how small and big firms adjust their macro expectations differently when the economy fluctuates.[17] The finding is that bigger firms are more likely to adjust their macro expectations than smaller firms when the GDP growth rate goes down. In the last three columns of Table 6, we use the GDP growth rate compared to the same quarter of last year to run the regressions and end up with qualitatively the same findings.

Next, we investigate how the likelihood of an update in the firm's sales expectation responds to fluctuations in the quarterly GDP growth rate. In the firm column of Table 7, we simply regress our (board) indicator for sales forecast revision, $FU^{sales,broad}_{t-1,t}$, on the GDP growth rate compared to the previous quarter and include firm fixed effects. The estimated coefficient is negative and statistically significant, which suggests that a slower GDP growth rate of increases the probability of adjusting firm's sales expectation. When we add the lagged firm size (the logarithm of registered capital) into the regression in column two, we find the same effect. Additionally, we find that bigger firms are less likely to update their sales forecasts, though the coefficient before firm size is insignificant and small. When we add industry-quarter and region-quarter fixed effects and investigate how small and big firms adjust their sales expectations differently when the economy fluctuates, we find that bigger firms are *less* likely to adjust their sales expectations than smaller firms when the GDP growth rate goes down. In the last three

[17] In this case, the direct effect of GDP growth on the probability of adjusting the macro expectation cannot be identified.

Table 6: Updating in macro expectation and GDP growth

	(1)	(2)	(3)	(4)	(5)	(6)
Dep.Var:	Indicator for macro expectation last quarter $\neq$ macro expectation this quarter					
gr prev qr	-1.124***	-1.124***				
	(0.075)	(0.075)				
lagged log size		-0.003	-0.005		-0.003	-0.004
		(0.003)	(0.003)		(0.003)	(0.003)
lagged log size X gr prev qr			-0.209***			
			(0.040)			
gr last qr				-0.836***	-0.836***	
				(0.038)	(0.038)	
lagged log size X gr last qr						-0.147***
						(0.022)
constant	0.300***	0.317***	0.330***	0.305***	0.323***	0.330***
	(0.000)	(0.020)	(0.020)	(0.000)	(0.020)	(0.020)
Industry FE	Yes	Yes	No	Yes	Yes	No
Region FE	Yes	Yes	No	Yes	Yes	No
Industry-quarter FE	No	No	Yes	No	No	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Region-quarter FE	No	No	Yes	No	No	Yes
N	382493	382493	382485	382493	382493	382485
R^2	0.258	0.258	0.282	0.258	0.258	0.282

* 0.10 ** 0.05 *** 0.01. Standard errors are clustered at the firm level, and all regression include firm fixed effects. We regress the indicator of updating macro expectation on GDP growth, firm size (lagged registered capital) and their interaction term. gr prev qr is the lagged quarterly growth rate compared to the previous quarter. gr last qr is the quarterly lagged growth rate compared to the same quarter of last year.

columns of Table 7, we use the GDP growth rate compared to the same quarter of last year to run the regressions. The findings are the same as in the first three columns *except* that bigger firms are shown to be *more* likely to adjust their sales expectations than smaller firms when the GDP growth rate goes down. In Table 12 of Appendix, we rerun all the above regressions by using our strict measure of sales forecast revision (i.e., $FU_{t-1,t}^{sales,strict}$). The estimation results are qualitatively the same.

Now, we turn to our second measure for information rigidity: the serial correlation of forecast errors. In the study of rational expectations models, whether forecast errors are serially correlated is used as a key test for the existence of information frictions (Mishkin (1983), Andrade and Le Bihan (2013), Coibion and Gorodnichenko (2012)). As agents know information perfectly in full information rational expectation (FIRE) models, ex post forecast errors are uncorrelated with any realized variable in FIRE models. In particular, a positive serial correlation of forecast errors indicates that the agent faces information constraints. Different from previous studies that focuses on macro-level forecasts (e.g., Andrade and Le Bihan (2013), Coibion and Gorodnichenko (2012), Coibion and Gorodnichenko (2015)), we focus on whether forecast errors of sales are correlated over time and how this correlation varies over the business cycles.

We first plot the serial correlation of forecast errors and the GDP growth relative to the same

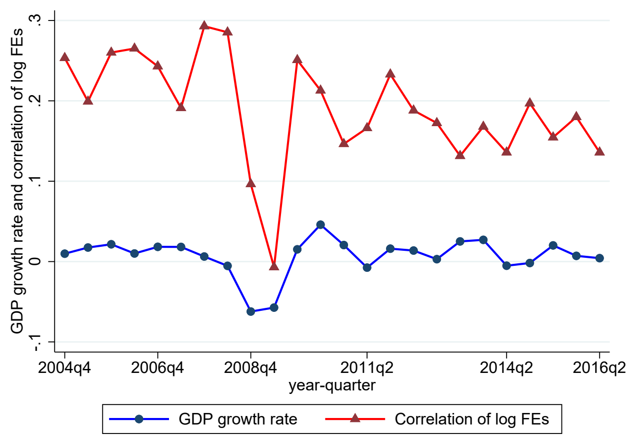
Table 7: Updating in sales forecast and GDP growth

	(1)	(2)	(3)	(4)	(5)	(6)
Dep.Var:	Indicator for sales forecast last quarter $\neq$ sales forecast this quarter					
gr prev qr	-0.710***	-0.711***				
	(0.077)	(0.077)				
lagged log size		-0.007**	-0.007*		-0.007**	-0.006
		(0.003)	(0.003)		(0.003)	(0.003)
lagged log size X gr prev qr			0.117***			
			(0.044)			
gr last qr				-0.789***	-0.789***	
				(0.038)	(0.038)	
lagged log size X gr last qr						-0.102***
						(0.022)
constant	0.623***	0.667***	0.660***	0.628***	0.673***	0.660***
	(0.000)	(0.021)	(0.021)	(0.000)	(0.021)	(0.021)
Industry FE	Yes	Yes	No	Yes	Yes	No
Region FE	Yes	Yes	No	Yes	Yes	No
Industry-quarter FE	No	No	Yes	No	No	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Region-quarter FE	No	No	Yes	No	No	Yes
N	364685	364685	364673	364685	364685	364673
R^2	0.262	0.262	0.286	0.263	0.263	0.286

* 0.10 ** 0.05 *** 0.01. Standard errors are clustered at the firm level, and all regressions include firm fixed effects. The indicator for an update in sales forecast is defined in a broad sense. We regress the indicator of updating sales forecast on GDP growth, firm size (lagged registered capital) and their interaction term. gr prev qr is the lagged quarterly growth rate compared to the previous quarter. gr last qr is the lagged quarterly growth rate compared to the same quarter of last year.

semi-year of last year from 2004 to 2016 in Figure 1.[18] It is clear that both the correlation and the GDP growth plummeted during the financial crisis (i.e., the second half of 2008 and the first half of 2009). Moreover, the time series of the two variables co-move over time, implying that the serial correlation of forecast errors becomes bigger when the GDP growth rate increases.

Figure 1: Correlation of Forecast Errors and GDP Growth



Note: Correlation of log forecast errors refers to the correlation (coefficient) between the current forecast error and last period's forecast error. GDP growth rates are presented in numbers (0.01 means 1% GDP growth relative to the same semi-year of last year). "q2" refers to the first semi-year, while "q4" refers to the second semi-year.

Next, we implement regression analysis by running the following regression equation:

$$FE_{i,t} = \beta_0 + \beta_1 FE_{i,t-1} + \beta_2 FE_{i,t-1} * GDP\ growth_{t-1} + \delta_{c,t} + \delta_{s,t} + \varepsilon_{i,t}, \tag{1}$$

where $GDP\ growth_{t-1}$ is the semi-year GDP growth rate of Japan (when the firm makes the forecast). We control for region-quarter fixed effects, $\delta_{r,t}$, and industry-quarter fixed effects, $\delta_{s,t}$, in the regression, which disable us to include the semi-year GDP rate into the explanatory variables of the above regression. In addition, we only utilize observations in the second or the fourth quarter to run the regressions as only observations in these two quarters report medium-term forecasts.

Two key regression results are report in Table 8. First, a positively significant coefficient of β_1 shows that forecast errors made in two adjacent periods are positively correlated conditional on zero GDP growth, which substantiates the existence of information frictions at the firm level.

[18]Note that as the forecast error of sales is defined at the frequency of semi-year level, we use semi-year GDP growth rate to measure economic fluctuations: the GDP growth rate compared to the previous semi-year (*grprevsemi*) and the GDP growth rate compared to the same semi-year of last year (*grlastsemi*).

Importantly, the estimated coefficient of β_2 is also positively significant, implying that this partial correlation increases when the GDP growth rate goes up. This implies that micro-level information frictions is pro-cyclical. If we change the GDP growth (from the previous semi-year) from -0.87% (the 10th. percentile) to 1.00% (the 90th. percentile), the correlation of (log and percentage) forecast errors would increase by 0.049, which is roughly 30% of the estimated coefficient, β_1. In short, a transition from the trough to the boom increases the correlation of forecast errors substantially.

Table 8: Serial correlation of forecast errors and GDP growth rate (domestic data): main results

	(1)	(2)	(3)	(4)
Dep.Var:	FE^{log}		FE^{pct}	
lagged FE^{log}	0.166***	0.167***		
	(0.007)	(0.007)		
lagged FE^{log} X gr last semi	0.826***			
	(0.231)			
lagged FE^{log} X gr prev semi		2.619***		
		(0.507)		
lagged FE^{pct}			0.164***	0.163***
			(0.007)	(0.007)
lagged FE^{pct} X gr last semi			0.507*	
			(0.263)	
lagged FE^{pct} X gr prev semi				2.629***
				(0.593)
constant	-0.008***	-0.008***	-0.001**	-0.001***
	(0.001)	(0.000)	(0.001)	(0.001)
Industry-quarter FE	Yes	Yes	Yes	Yes
Region-quarter FE	Yes	Yes	Yes	Yes
N	94620	94620	94716	94716
R^2	0.124	0.124	0.115	0.116

* 0.10 ** 0.05 *** 0.01. Standard errors are clustered at the firm level. We regress the forecast error on the lagged forecast error and its interaction term with the semi-year GDP growth rate. Top and bottom one percent of forecast errors are trimmed. gr prev semi is the lagged semi-year growth rate compared to the previous semi-year. gr last semi is the lagged semi-year growth rate compared to the same semi-year of last year. FE^{log} is the log deviation of the realized sales from the projected sales, while FE^{pct} is the percentage deviation of the realized sales from the projected sales. All regressions control for industry-quarter and region-quarter fixed effects. This regression is at the semi-year frequency, and forecasts made in the second quarter and the fourth quarter are used.

We implement two robustness checks. First, we run the regression equation 1 using the residual percentage forecast error and the residual log forecast error. The results are presented in Table 13. Next, we utilize surviving firms only: firms that have appeared in the dataset for at least eight consecutive quarters.[19] The results are presented in Table 14. Both robustness checks confirm our finding.

In total, we document that firms update expectations more frequently and make less correlated forecast errors when the economic growth rate drops. These findings hint that the degree

[19] These firms are dominantly big firms.

of information rigidity goes down when the macro-economy tanks.

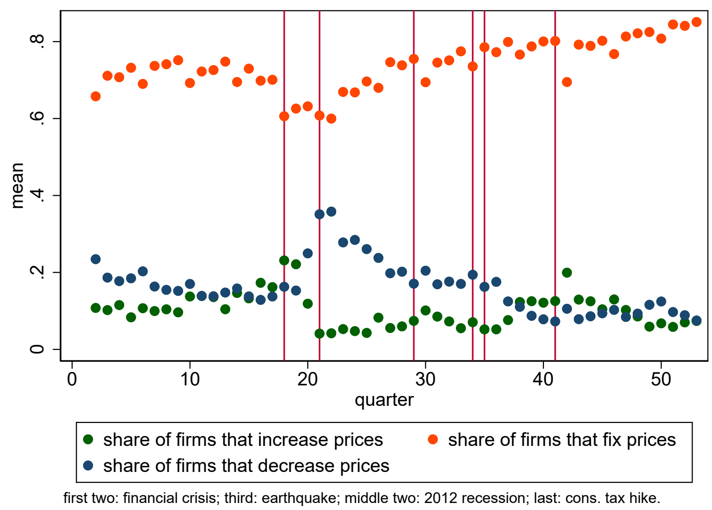
2.5 Fact Three: Counter-cyclical frequency of price adjustment

In this subsection, we analyze the cyclical properties of price adjustment. We found that price adjustment is counter-cyclical, a pattern that is similar to what Vavra (2013) documents using product-level data from the U.S. Although the overall frequency of price adjustment is informative about price rigidity, we *cannot* conclude that counter-cyclical frequency of price adjustment implies pro-cyclical price rigidity. Intuitively, the fraction of firms that adjust output prices depends positively on two factors: the volatility of (demand/supply) shocks and the *sensitivity* of output price adjustment to shocks. Firms are more likely to adjust output prices, as long as one of the two factors increases. We view the second factor as the measure for price stickiness, as the first factor in most models (as in our model in the this paper) is assumed to evolve exogenously. After all, there would be no firms that change output prices, if there were no shocks (to their demand/supply conditions) over time. And, we cannot conclude that price rigidity is extremely high in this hypothetical case, as there is no need to adjust output prices in this case.

Under our definition, prices can become more rigid even if the over all frequency of price adjustment increases, as long as the increase in the volatility of shocks dominates the decrease in the sensitivity of output price adjustment to shocks. Fortunately, we have information on both whether the firm adjusts output price *and* whether the firm receives a shock to its input price or demand (i.e., whether the input price and firm-specific demand change from last quarter to current quarter). Therefore, we can study both how the GDP growth rate affects the likelihood of firm's changing its output price and the sensitivity of output price adjustment to demand/cost shocks.

We start the analysis by simply plotting how the fraction of firms that fix or increase or decrease their output prices (from last quarter to current quarter) evolves over time in Figure 2. The number on the horizontal axis refers the quarter (1,2... starting from 2004/Q1). Three observations are worth mentioning. First, the fraction of firms that fix output prices in two consecutive quarters is quite high ($75\% - 80\%$) and has an increasing trend over time. Second, the fraction of firms that fix output prices had dropped substantially during the financial crisis and slightly during the 2012 recession (2012/Q2-Q3). Moreover, both the fraction of firms that increase prices and the fraction of firms that decrease prices had increased during these two recessions. Finally, the fraction of firms that fix output prices also dropped substantially after the 2011 Tohoku earthquake (the end of 2011/Q1) and the consumption hike on April/1/2014. Similar to the experience during the two recessions, both the fraction of firms that increase prices and the fraction of firms that decrease prices increased immediately after these two big negative events. The possible candidate for this two-way movements of prices is the increasing volatility of firm-level and/or macro shocks during recessions and after big negative events, which we will show in the next subsection.[20]

Figure 2: Time-series plot of output price adjustments



Note: This figure plots how the fraction of firms that fix or increase or decrease their output prices (from last quarter to current quarter) evolves over time.

Although Figure 2 seems to suggest that the level of price stickiness goes down during recessions, we still have to investigate how the sensitivity of output price adjustment to demand/cost shocks. We run the following regression:

$$\begin{aligned} output\ price^{stick}_{i,t} &= \beta_0 + \beta_1 input\ price^{stick}_{i,t} + \beta_2 GDP\ growth_{t-1} \\ &\quad + \beta_3 input\ price^{stick}_{i,t} * GDP\ growth_{t-1} + \delta_r + \delta_s + \delta_i + \varepsilon_{i,t}, \end{aligned} \tag{2}$$

where $GDP\ growth_{t-1}$ is the quarterly GDP growth rate of the previous quarter, and $output\ price^{stick}_{i,t}$ and $input\ price^{stick}_{i,t}$ are the indicator functions for whether the firm changes its output price and bear a change in its input price in the current. We control for region-quarter fixed effects, δ_r, and industry-quarter fixed effects, δ_s, in the regression. In some of the regressions, we also control for region-quarter fixed effects, $\delta_{r,t}$, industry-quarter fixed effects, $\delta_{s,t}$, and/or lagged firm size. In the explanatory variables, we use two proxies to measure economic fluctuations: the GDP growth rate compared to the previous quarter (*grprevqr*) and the GDP growth rate

[20] In Figure 5 of Appendix, we plot how the fraction of firms that fix or increase or decrease their input prices (from last quarter to current quarter) evolves over time. The findings are qualitatively the same as those documented for the output prices.

compared to the same quarter of last year ($grlastqr$).

We report the regression results in Table 9. First, when the firm receive a change in its input price, it is more likely to adjust its output price. This is shown by a positively significant estimate, β_1. As the estimated coefficient β_1 is below one, the output price adjustment (after a shock to the input price) is incomplete, which is evident for the existence of (output) price rigidity.[21] Second, the direct effect of a drop in the GDP growth rate on the likelihood of adjusting the output price is negatively estimated, shown by β_2. This is consistent with our finding in Figure 2. What is interesting is that the interaction term between the input price change and the quarterly GDP growth rate (β_3) is also negatively significant. This implies that conditioning on a change in the input price, firms are more likely to adjust their output prices when the GDP growth rate drops. The above three findings are robust to using different ways of measure the GDP growth rate, the inclusion of lagged firm size, and the usage of industry-quarter and region-quarter fixed effects.[22]

Table 9: Sensitivity of output price change to input price change and economic fluctuation

	(1)	(2)	(3)	(4)	(5)	(6)
Dep.Var:	Indicator (output price(t)≠ price(t-1))					
input price(t)≠input price(t-1)	0.315***	0.318***	0.315***	0.318***	0.313***	0.315***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
gr prev qr	-1.036***		-1.035***			
	(0.061)		(0.061)			
input price(t)≠input price(t-1) X gr prev qr	-0.865***		-0.865***		-0.320**	
	(0.133)		(0.133)		(0.151)	
gr last qr		-0.646***		-0.646***		
		(0.033)		(0.033)		
input price(t)≠input price(t-1) X gr last qr		-0.486***		-0.486***		-0.350***
		(0.076)		(0.076)		(0.080)
lagged log firm size			0.001	0.001	-0.002	-0.002
			(0.003)	(0.003)	(0.003)	(0.003)
constant	0.152***	0.155***	0.145***	0.150***	0.161***	0.161***
	(0.001)	(0.001)	(0.020)	(0.020)	(0.020)	(0.020)
Industry FE	Yes	Yes	Yes	Yes	No	No
Region FE	Yes	Yes	Yes	Yes	No	No
Industry-quarter FE	No	No	No	No	Yes	Yes
Region-quarter FE	No	No	No	No	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
N	349720	349720	349720	349720	349697	349697
R^2	0.482	0.482	0.482	0.482	0.498	0.498

* 0.10 ** 0.05 *** 0.01. Standard errors are clustered at the firm level, and all regressions include firm fixed effects. We regress the indicator of adjusting output price on the indicator of changing input price, the lagged quarterly GDP growth rate, and their interaction term. gr prev qr is the lagged quarterly growth rate compared to the previous quarter. gr last qr is the lagged quarterly growth rate compared to the same quarter of last year.

[21] Note that the average quarterly GDP growth rate is near zero 0.1% on average during 2004-2016.

[22] In Table 15 of Appendix, we run equation 2 by replacing $input\ price^{stick}_{i,t}$ by the expected change in firm-specific demand conditions. The estimation results are qualitatively the same as in Table 9.

As before, the adjustment in output price and the change in input price might be jointly determined by the firm. Therefore, it is not clear whether the change in the input price is the cause of the adjustment in the output price (or the other way around). In order to address this issue, we use firm's expected change in macroeconomic conditions (i.e., $Fore_t(macro_t)$) to run the regression, as it is unlikely that a single firm can change the overall macroeconomic conditions by adjusting its price. The regression results reported in Table 10 are qualitatively the same as in Table 9. In total, we conclude that the level of price rigidity goes down when the GDP growth rate drops, as both the fraction of firms that adjust output prices and the sensitivity of output price adjustment to cost/demand/macro shocks go up.

Table 10: Sensitivity of output price change to firm-specific demand change and economic fluctuation

	(1)	(2)	(3)	(4)	(5)	(6)
Dep.Var:	Indicator (output price (t) $\neq$ output price (t-1))					
macro demand(t)$\neq$macro demand(t-1)	0.137***	0.139***	0.137***	0.139***	0.130***	0.133***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
gr prev qr	-0.751***		-0.751***			
	(0.060)		(0.060)			
macro demand(t)$\neq$macro demand(t-1) X gr prev qr	-0.697***		-0.697***		-0.455***	
	(0.104)		(0.104)		(0.129)	
gr last qr		-0.303***		-0.303***		
		(0.035)		(0.035)		
macro demand(t)$\neq$macro demand(t-1) X gr last qr		-0.595***		-0.595***		-0.521***
		(0.064)		(0.064)		(0.067)
lagged log firm size			0.000	0.000	-0.003	-0.003
			(0.003)	(0.003)	(0.003)	(0.003)
constant	0.195***	0.196***	0.194***	0.196***	0.215***	0.214***
	(0.001)	(0.001)	(0.020)	(0.020)	(0.020)	(0.020)
Industry FE	Yes	Yes	Yes	Yes	No	No
Region FE	Yes	Yes	Yes	Yes	No	No
Industry-quarter FE	No	No	No	No	Yes	Yes
Region-quarter FE	No	No	No	No	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
N	379790	379790	379790	379790	379770	379770
R^2	0.430	0.430	0.430	0.430	0.448	0.448

* 0.10 ** 0.05 *** 0.01. Standard errors are clustered at the firm level, and all regressions include firm fixed effects. We regress the indicator of adjusting output price on the indicator of changing firm-specific demand, the lagged quarterly GDP growth rate, and their interaction term. gr prev qr is the lagged quarterly growth rate compared to the previous quarter. gr last qr is the lagged quarterly growth rate compared to the same quarter of last year.

2.6 Fact Four: Counter-cyclical volatility of sales growth and forecast errors

In this subsection, we explore how the volatility of firm-level variables move over the business cycles. Following existing studies of uncertainty shocks (e.g., Kehrig (2015) and Bloom et al. (2018)), we look at the cross-sectional variance of sales growth rates in the domestic survey. At the mean time, we also investigate how the variance of log forecast errors varies over time. Table 11 presents how the (semi-year) GDP growth rate is correlated with the standard deviation of firms' sales growth and with the variance of forecast errors from 2004/2nd. half-2016/1st. half. Although we have a limited number of observations, the table shows that the GDP growth rate negatively affects both the volatility of firm-level sales growth rates and the standard deviation of forecast errors. These findings are consistent with those documented in Kehrig (2015), Bloom et al. (2018) and Tanaka et al. (2018).

Table 11: Correlation between GDP growth rate and firm-level growth and volatility

	(1) GDP growth rate (semi-year)
average log sales	0.39*
N	24
std. dev. of log sales growth	-0.38*
N	24
std. dev. of log forecast errors	-0.47**
N	24

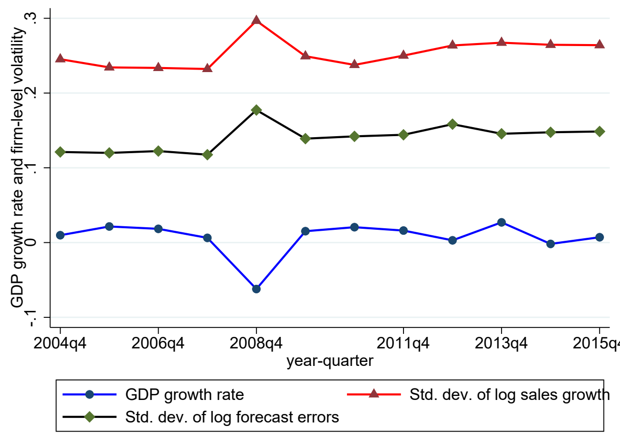
Note: GDP growth rate refers to the growth relative to the same semi-year of last year. We calculate average log sales, standard deviation of log sales growth and standard deviation of log forecast errors (of all firms) semi-year by semi-year (from 2004/2nd. half-2016/1st. half). Top and bottom one percent of observations are trimmed, whenever we calculate aggregate statistics based on firm-level variables. * 0.10 ** 0.05 *** 0.01.

Figure 3 and 4 present how the GDP growth rate and average firms' sales growth rates (in our sample) evolve over time. In addition, the two figures also show how the cross-sectional variance of sales growth rates and that of the forecast errors evolve over time in our domestic survey. Consistent with the findings documented in Table 11, the GDP growth rate and average sales growth of firms move in the opposite directions relative to the movement of the cross-sectional variance of sales growth rates and that of forecast errors. These two figures reassure that volatility of firm growth is counter-cyclical.[23]

In summary, we find that when the GDP growth goes down, the variance of forecast errors increases while the level of information frictions decreases. Therefore, we argue that it is the substantial increase in the volatility of firm-level "real shocks" such as productivity/demand shocks that triggers counter-cyclical volatility of firm-level variables, not the increase in the variance of firm-level noises that are related to information frictions.

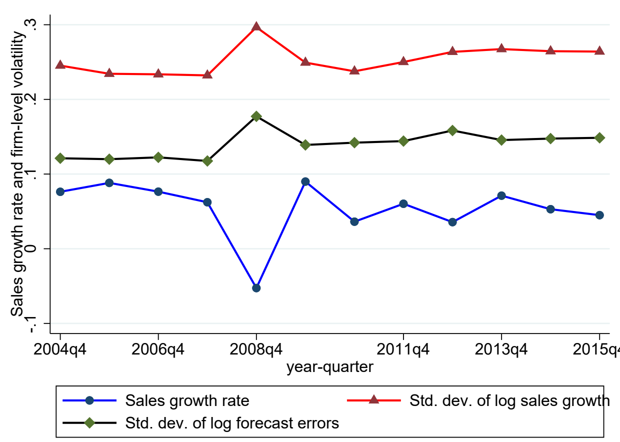
[23] The reason why we only plot aggregate statistics for the second half of each year is that the sampling frame (of small and medium-sized firms) changes at the beginning of each fiscal year (i.e., the second quarter). As a result, the sample size shrinks substantially, when we calculate various aggregate statistics (based on firm-level variables) in the first half of each fiscal year.

Figure 3: Counter-cyclical firm-level volatility



Note: GDP growths are presented in numbers (0.01 means 1% GDP growth relative to the same semi-year of last year). "q4" refers to the second semi-year.

Figure 4: Firm-level volatility and firm-level sales growth



Note: Log sales growth rate is the average log sales growth rate of all firms in a given semi-year. "q4" refers to the second semi-year.

3 A Model

In this section, we present a simple two-period partial equilibrium model that features imperfect information and endogenous acquisition of information in order to rationalize the first three stylized facts documented above.

3.1 Setup

We consider a two-period model with the quasi-linear demand function. Following Melitz and Ottaviano (2008), we assume that the firm's demand function is

$$q = (a_i + \tau) - \gamma p, \tag{3}$$

where p and q are the firm's price and output (i.e., quantity demanded) respectively. Variable a_i is the firm's demand shifter in period i ($i = 1$ or 2) and uniformly distributed on $[\bar{a} - \sigma_a, \bar{a} + \sigma_a]$ with the PDF (probability density function) of $\frac{1}{2\sigma_a}$ such that $\bar{a} - \sigma_a > 0$. For simplicity, we assume that the firm's demand is $\bar{a}$ in the first period ($a_1 = \bar{a}$) and the firm knows it. In the beginning of the second period, the firm makes a demand draw from the uniform distribution $U(\bar{a} - \sigma_a, \bar{a} + \sigma_a)$ where the mean is its realized demand in the first period. Thus, the demand shock in the second period is $a - \bar{a}$. Parameter $\tau(> 0)$ captures aggregate demand conditions which are positively related to the average price of all active firms. A lower average price charged by all firms leads to tough competition and thus a smaller τ. The slope of the demand function, $\gamma(> 0)$, is determined by the market size (i.e., the population of the economy) and the substitutability between varieties (i.e., goods). Specifically, a bigger market size or a higher level of substitutability between varieties leads to a steeper slope. As we consider the problem of a single firm and focuses on the effect of second moment shocks, both γ and τ are taken as given.

The firm has to pay the production cost in order to produce in both periods. Specifically, the firm faces a constant marginal cost of production, c_0. As a result, the total production cost is

$$TC(q) = c_0 q, \tag{4}$$

where c_0 also includes the wage rate. The cost shifter is assumed to be fixed across two periods. In the second period, the firm pays another two costs if necessary: the cost of acquiring information and the cost of adjusting the price. First, the firm can acquire information about its second-period demand by paying the following cost:

$$IC(\lambda) = c_1\lambda. \tag{5}$$

where c_1 is the marginal cost of acquiring information and $\lambda \geq 0$ is the intensity of acquiring information. As a result, the firm observes the demand shock, a_2, with probability $1 - e^{-b\lambda}$. With probability $e^{-b\lambda}$, the firm does not obtain information about a_2 and therefore sticks to the prior belief: $U(\bar{a} - \sigma_a, \bar{a} + \sigma_a)$.[24] The third cost the firm may pay is the fixed cost of adjusting its price in the second period which is denoted by $\kappa(> 0)$. The key parameter of interest is how an increase in the variance of demand shocks, σ_a, affects information acquisition and pricing.

We adopt the following assumption to make sure that the firm survives irrespective the demand shifter it has, if it can set the price flexibly:

Assumption 1

$$\bar{a} - \sigma_a + \tau \geq c_0\gamma.$$

The above assumption imposes an upper bound on the marginal cost of production. If it is violated, the firm with a sufficiently small value of a_2 would stop producing, when it has discovered its demand shifter in the second period. Next, we adopt the following assumption to make sure that firms with sufficiently high or low demand shifters do adjust their prices when they observe their demand shifters in the second period:

Assumption 2

$$\sigma_a^2 \geq 4\gamma\kappa; \quad (\bar{a} - \sigma_a + \tau - c_0\gamma)^2 \geq 4\gamma\kappa.$$

The above assumption requires that the adjustment cost of output price is small enough.

There are two reasons why we introduce uncertainty to the demand side. First, there is information on expected change in firm-specific/macro demand in the data. Thus, introducing demand-side uncertainty enables us to utilize the data. Second, if we only had uncertainty at the supply side (i.e., costs), firm's demand would be perfectly known after the firm has chosen its price (which is the choice variable in our model). Note that the firm forecasts its sales and chooses the output price at the same time in the model (and in the data). Therefore, there would

[24] As the marginal effect of an increase in λ on the probability of observing a_2 approaches infinity when λ goes to zero, it is always optimal for the firm to choose an intensity that is strictly positive.

be no forecast error of sales, if we only had uncertainty at the supply side. This is inconsistent with the data.

We choose to use the quasi-linear demand function, as we have demand-side uncertainty and a constant marginal cost. In order to incentivize the firm to acquire information, it has to be the case that optimal price which is the firm's choice variable depends on whether the firm knows its demand. If we adopted the CES demand function with a constant marginal cost, optimal price would only depend on the firm's marginal cost which the firm knows and does not depend on whether the firm knows its demand. Thus, there would be no incentive for the firm to acquire information in order to price optimally. There are two ways to solve this problem. The first solution is to use a demand function that features a non-constant markup which is the approach we adopt in this paper. An alternative solution is to use the CES demand function with an increasing marginal cost, in which case the optimal price depends on the quantity produced and accordingly the demand shifter. We choose the first approach, as it is simpler in the sense that we can obtain a closed-form solution of the optimal price.

3.2 Analysis

We solve the optimization problem in the first period first. Suppose the firm chooses a price that maximizes its static profit in the first period.[25] As a result, the objective function in the first period becomes

$$\max_{p} \quad (p - c_0)[(\bar{a} + \tau) - \gamma p], \tag{6}$$

which leas to the result that

$$p_1 = \frac{\bar{a} + \tau}{2\gamma} + \frac{c_0}{2}, \tag{7}$$

which is bigger than c_0 (thanks to Assumption 1) and positively depends on the firm-specific demand condition, $\bar{a}$. The resulting profit in the first period is

$$\pi_1 = \frac{1}{4\gamma}\big(\bar{a} + \tau - \gamma c_0\big)^2. \tag{8}$$

Now, we analyze the firm's problem of acquiring information and choosing the output price in the second period. The analysis consists of two parts: the determination of the intensity of acquiring information (in the first stage) and optimal pricing (in the second stage) given the information structure (i.e., whether the demand in the second period is observed). We analyze the pricing behavior in the second stage first. The optimization problem of setting the price

[25] Reis (2006) shows that the firm is indifferent between choosing the price first and choosing the quantity first under the quasi-linear demand function with an uncertain demand shifter.

without taking into account the fixed cost of price adjustment is

$$\max_{p} \quad E\Big[(p - c_0)\big((a_2 + \tau) - \gamma p\big)\Big], \tag{9}$$

where E means taking the expectation. The resulting optimal price is

$$p_2 = \frac{Ea_2 + \tau}{2\gamma} + \frac{c_0}{2}, \tag{10}$$

in which $Ea_2 = \bar{a}$ if the firm does not observe the demand shifter in the second period and $Ea_2 = a_2$ if the firm does observe it. In total, the *realized* profit in the second period is

$$\pi_2 = \frac{1}{4\gamma}\Big[(Ea_2 + \tau - \gamma c_0)(2a_2 - Ea_2 + \tau - \gamma c_0)\Big], \tag{11}$$

which is maximized when $Ea_2 = a_2$.

In order to facilitate analysis, we make two simplifying notations. First, we denote the second period's profit under perfect information with price adjustment as

$$\pi_2^{per,adj}(a_2) = \frac{1}{4\gamma}\big(a_2 + \tau - \gamma c_0\big)^2 - \kappa. \tag{12}$$

Second, we denote the second period's profit under perfect information *without* price adjustment as

$$\pi_2^{per,no}(a_2) = \frac{1}{4\gamma}\Big[(\bar{a} + \tau - \gamma c_0)(2a_2 - \bar{a} + \tau - \gamma c_0)\Big]. \tag{13}$$

By comparing equations (12) with (13), we conclude that the firm adjusts its price from p_1 (as defined in equation (7)) to

$$p_2 = \frac{a_2 + \tau}{2\gamma} + \frac{c_0}{2},$$

if and only if

$$(a_2 - \bar{a})^2 \geq 4\gamma\kappa, \tag{14}$$

which leads to the lower and upper bounds on the realized demand shifter, a_2, beyond which the firm adjusts its price:

$$\underline{a}_2 = \bar{a} - 2\sqrt{\gamma\kappa} \tag{15}$$

and

$$\overline{a}_2 = \bar{a} + 2\sqrt{\gamma\kappa}. \tag{16}$$

Assumption 2 assures that

$$\bar{a} - \sigma_a \leq \underline{a}_2 < \bar{a} < \overline{a}_2 \leq \bar{a} + \sigma_a.$$

The following proposition characterizes the optimal pricing behavior in the second stage when the demand condition is observed:

Proposition 1 *The firm's pricing strategy follows a "Ss" rule: (1) When the demand condition is not observed, the firm does not change its price. (2) When the demand condition is observed, the firm changes the price from* $\frac{\bar{a}+\tau}{2\gamma} + \frac{c_0}{2}$ *to* $\frac{a_2+\tau}{2\gamma} + \frac{c_0}{2}$*, if and only if the realized demand shifter lies outside the interval of* $[\underline{a}_2, \overline{a}_2]$ *where they are determined by equations (15) and (16). Finally, it is optimal for the firm to choose the price of* $\frac{\bar{a}+\tau}{2\gamma} + \frac{c_0}{2}$ *to maximize the static profit in the first period.*

Proof. See Appendix 5.1.1. ■

The above pricing strategy is closely related to the "Ss" policy proposed in Barro (1972). A key observation from our proposition is that both $\underline{a}_2$ and $\overline{a}_2$ do not vary with the variance of the demand shifter (i.e., σ_a). As the second period is assumed to be the ending period, the typical "wait-and-see" effect (equivalently the options-value effect) disappears.[26]

Next, we analyze how the firm chooses the intensity of acquiring information in the first stage. The benefit of acquire information about a_2 is that with probability $1 - e^{-b\lambda}$, the firm is going to know a_2 and accordingly changes its output price if a_2 is outside the inaction region. In mathematical terms, we can write the benefit of acquiring information minus the cost of acquiring ti as

$$\begin{aligned} L(\lambda, \sigma_a) \equiv (1 - e^{-b\lambda}) \Big(\int_{\bar{a}-\sigma_a}^{\underline{a}_2} \left[\pi_2^{per,adj}(a_2) - \pi_2^{per,no}(a_2) - \kappa\right] \frac{1}{2\sigma_a} da_2 \\ + \int_{\overline{a}_2}^{\bar{a}+\sigma_a} \left[\pi_2^{per,adj}(a_2) - \pi_2^{per,no}(a_2) - \kappa\right] \frac{1}{2\sigma_a} da_2 \Big) - c_1\lambda. \end{aligned} \tag{17}$$

The optimal choice of λ is determined by

$$\frac{\partial L(\lambda, \sigma_a)}{\partial \lambda} = 0,$$

[26] In an infinite horizon model, the inaction region of not changing the price would expand after second moment shocks. However, this effect is small (relative to the increase in the variance of the shock), as pointed out by Vavra (2013).

or

$$be^{-b\lambda}\Big(\int_{\bar{a}-\sigma_a}^{\underline{a}_2}\left[\pi_2^{per,adj}(a_2)-\pi_2^{per,no}(a_2)-\kappa\right]\frac{1}{2\sigma_a}da_2$$
$$+\int_{\overline{a}_2}^{\bar{a}+\sigma_a}\left[\pi_2^{per,adj}(a_2)-\pi_2^{per,no}(a_2)-\kappa\right]\frac{1}{2\sigma_a}da_2\Big)-c_1=0 \tag{18}$$

As the marginal benefit of acquiring information declines monotonically from infinity to zero when λ varies from zero to infinity, we have a unique solution of $\lambda^*(\sigma_a)$.

3.3 Second Moment Shock

Having established the "Ss" pricing policy, we proceed to study how a mean-preserving spread (i.e., an increase in σ_a) affects the information acquisition and the frequency of the price adjustment. Total differentiation of equation (18) with respect to λ and σ_a yields

$$\frac{d\lambda^*(\sigma_a)}{d\sigma_a}=-\frac{\frac{\partial^2 L(\lambda,\sigma_a)}{\partial\sigma_a\partial\lambda}}{\frac{\partial^2 L(\lambda,\sigma_a)}{\partial\lambda^2}}.$$

The second order condition tells us that

$$\frac{\partial^2 L(\lambda,\sigma_a)}{\partial\lambda^2}<0.$$

Therefore, we have

$$\frac{d\lambda^*(\sigma_a)}{d\sigma_a}\geq 0$$

if and only if

$$\frac{\partial^2 L(\lambda,\sigma_a)}{\partial\sigma_a\partial\lambda}>0.$$

The following proposition studies how a second moment shock affects the information acquisition and the frequency of price adjustment.

Proposition 2 *An increase in the variance of demand shocks leads to three results. First, the intensity of information acquisition goes up. As a result, the firm updates its demand/sales expectations more frequently. Second, conditional on an update in demand/sales expectations, the firm is more likely to change the output price. Finally, the overall probability of price adjustment goes up.*

Proof. See Appendix 5.1.2. ■

The intuition behind the above proposition is straightforward. Obtaining information is valuable, only when the realized demand shifter is far away from the prior (i.e., the demand shifter that leads to the price chosen in the first period) which leads to a more likely price adjustment. When the variance of the demand shifter increases, the probability of a price change *conditioning* on observing the demand increases. Moreover, the benefit of adjusting the price after the firm decides to change the price increases on average, as the realized demand shifter a_2 is, on average, further away from the demand shifter in the first period. These two forces increase the marginal benefit and thus the incentive of acquiring information, when the variance of demand shifter increases.

3.4 First Moment Shock

One surprising result is that a decrease in the mean of demand shifter, $\bar{a}$ (i.e., a first moment shock), has no effect on the firm's incentive to acquire information in our benchmark model. This is true, as both the benefit and the cost of adjusting the price are independent of the mean of the demand shifter. Specifically, the spread of the inaction region (i.e., $[\underline{a}_2, \overline{a}_2]$) moves in the same direction and by the same degree with the mean of the demand shifter. In order to solve this problem, we introduce a fixed cost of operation, f, in order to generate the possibility of receiving negative profits. Crucially, the firm is assumed to pay this fixed cost *after* the (possible) revelation of the demand shifter in the second period. As a result, there is an extra benefit of acquiring information. That is, the firm can avoid paying this fixed cost by not producing, if it has discovered that the demand shifter is too low.[27] This extra benefit of acquiring information naturally increases in recessions, as the likelihood of drawing a demand shifter that leads to a negative realized profit increases in recessions. In order to generate the possibility of receiving negative profits under perfect information, we assume that

Assumption 3

$$\frac{1}{4\gamma}\left(\bar{a} - \sigma_a + \tau - \gamma c_0\right)^2 < f,$$

which implies that the firm chooses to not produce (without paying the fixed operation cost), if it has discovered that its demand shifter in the second is at its minimum level. Furthermore, we assume that it is profitable for the firm to operate, if the realized or the expected demand is at its prior mean:

[27] We assume that firms can stop production but stay in the market for at least one period. Alternatively, readers can think these firms as firms that exit the market for one period.

Assumption 4

$$\frac{1}{4\gamma}\big(\bar{a}+\tau-\gamma c_0\big)^2 > f,$$

which implies that it is profitable for the firm to operate in the first period as $a_1 = \bar{a}$, and to operate in the second period if it fails to acquire any information concerning a_2.

3.4.1 Pricing

We now discuss how the firm's pricing strategy in the second period behaves in the world with a fixed operation cost. If the firm ends up not observing its demand shifter in the second period, it is going to stick to the price that is charged in the first period and proceed to produce as

$$E\pi_2^{per,no}(a_2) = \frac{1}{4\gamma}\int_{\bar{a}-\sigma_a}^{\bar{a}+\sigma_a}\Big[(\bar{a}+\tau-\gamma c_0)(2a_2-\bar{a}+\tau-\gamma c_0)\Big]\frac{da_2}{2\sigma_a} = \frac{1}{4\gamma}(\bar{a}+\tau-\gamma c_0)^2 > f.$$

Next, if the firm ends up knowing its demand shifter in the second period, we have the same indifference condition that pins down the inaction region of the price change as in equation (14). What is new here is that there is another condition that pins down the zero-profit threshold that makes the firm not produce in the second period:

$$\tilde{a}_2 = \min(\tilde{a}_{21}, \tilde{a}_{22}), \tag{19}$$

where $\tilde{a}_{21}$ and $\tilde{a}_{22}$ satisfy the following conditions respectively:

$$\frac{1}{4\gamma}(\tilde{a}_{21}+\tau-\gamma c_0)^2 - \kappa = f; \tag{20}$$

$$\frac{1}{4\gamma}\Big[(\bar{a}+\tau-\gamma c_0)(2\tilde{a}_{22}-\bar{a}+\tau-\gamma c_0)\Big] = f. \tag{21}$$

Based on the above two conditions, we have two cases to consider. First, when $\tilde{a}_{21} \leq \underline{a}_2$, we have

$$\tilde{a}_2 = \tilde{a}_{21},$$

and there are firms that reduce their prices and firms that do not produce. When $\tilde{a}_{21} > \underline{a}_2$, there are no firms that reduce their prices, as the choice of reducing the output price is dominated either by not producing (when the demand shifter is low) or by fixing the price (when the demand shifter is in the middle range). The following proposition characterizes the pricing strategies in these two cases

Proposition 3 *When the fixed operation cost is small:*

$$\bar{a} - 2\sqrt{\gamma\kappa} > 2\sqrt{\gamma(f+\kappa)} + \gamma c_0 - \tau,$$

we have four types of firms: (1) for firms with $a_2 \in (\overline{a}_2, \bar{a} + \sigma_a]$*, the price increases from* $\frac{\bar{a}+\tau}{2\gamma} + \frac{c_0}{2}$ *to* $\frac{a_2+\tau}{2\gamma} + \frac{c_0}{2}$*; (2) for firms with* $a_2 \in [\underline{a}_2, \overline{a}_2]$*, the price is unchanged; (3) for firms with* $a_2 \in [\tilde{a}_{21}, \underline{a}_2)$*, the price is reduced from* $\frac{\bar{a}+\tau}{2\gamma} + \frac{c_0}{2}$ *to* $\frac{a_2+\tau}{2\gamma} + \frac{c_0}{2}$*; (4) for firms with* $a_2 \in [\bar{a} - \sigma_a, \tilde{a}_{21})$*, they do not produce and thus earn zero profit.*
When the fixed operation cost is high:

$$\bar{a} + 2\sqrt{\gamma\kappa} > 2\sqrt{\gamma(f+\kappa)} + \gamma c_0 - \tau \geq \bar{a} - 2\sqrt{\gamma\kappa},$$

we have three types of firms: (1) for firms with $a_2 \in (\overline{a}_2, \bar{a} + \sigma_a]$*, the price increases from* $\frac{\bar{a}+\tau}{2\gamma} + \frac{c_0}{2}$ *to* $\frac{a_2+\tau}{2\gamma} + \frac{c_0}{2}$*; (2) for firms with* $a_2 \in [\tilde{a}_{22}, \overline{a}_2]$*, the price is unchanged; (3) for firms with* $a_2 \in [\bar{a} - \sigma_a, \tilde{a}_{22})$*, they do not produce and earn zero profit. The four cutoffs,* $\underline{a}_2$*,* $\overline{a}_2$*,* $\tilde{a}_{21}$ *and* $\tilde{a}_{22}$*, are pinned down by equations (15), (16), (20) and (21) respectively.*

Several points are worth mentioning. First, if the fixed operation cost, f, were zero. we must have

$$\bar{a} - 2\sqrt{\gamma\kappa} \geq \bar{a} - \sigma_a \geq 2\sqrt{\gamma\kappa} - \tau + c_0\gamma,$$

which is true under Assumption 2. Therefore, we must be in the first case discussed above and there are no firms that choose to not produce. In other words, we are back to our benchmark model. Second, compared to the model without the fixed operation cost, there is another incentive for the firm to acquire information now. That is, the firm can avoid paying the fixed operation cost if its demand shiter turns out to be sufficiently low and the firm observes it.

3.4.2 Information Acquisition

Next, we can analyze how the firm chooses the intensity of acquiring information in the first stage. The benefit of acquiring information about a_2 is that with probability $1 - e^{-b\lambda}$, the firm is going to know a_2 and accordingly changes its output price (when a_2 is outside the inaction region) or stop producing (when a_2 is below the zero-profit threshold). As implies by Proposition 3, we have two cases to consider. First, when $\bar{a} - 2\sqrt{\gamma\kappa} > 2\sqrt{\gamma(f+\kappa)} + \gamma c_0 - \tau$, we can write the benefit of acquiring information minus the cost of acquiring information as

$$L(\lambda, \bar{a}) \equiv (1 - e^{-b\lambda})\Big(\int_{\bar{a}-\sigma_a}^{\tilde{a}_{21}} \big[f - \pi_2^{per,no}(a_2) \big] \frac{1}{2\sigma_a} da_2 + \int_{\tilde{a}_{21}}^{\underline{a}_2} \big[\pi_2^{per,adj}(a_2) - \pi_2^{per,no}(a_2) - \kappa \big] \frac{1}{2\sigma_a} da_2$$
$$+ \int_{\bar{a}_2}^{\bar{a}+\sigma_a} \big[\pi_2^{per,adj}(a_2) - \pi_2^{per,no}(a_2) - \kappa \big] \frac{1}{2\sigma_a} da_2 \Big) - c_1\lambda. \tag{22}$$

The optimal choice of λ at stage one of the second period is determined by

$$be^{-b\lambda}\Big(\int_{\bar{a}-\sigma_a}^{\tilde{a}_{21}} \big[f - \pi_2^{per,no}(a_2) \big] \frac{1}{2\sigma_a} da_2 + \int_{\tilde{a}_{21}}^{\underline{a}_2} \big[\pi_2^{per,adj}(a_2) - \pi_2^{per,no}(a_2) - \kappa \big] \frac{1}{2\sigma_a} da_2$$
$$+ \int_{\bar{a}_2}^{\bar{a}+\sigma_a} \big[\pi_2^{per,adj}(a_2) - \pi_2^{per,no}(a_2) - \kappa \big] \frac{1}{2\sigma_a} da_2 \Big) - c_1 = 0,$$

which is equivalent to

$$be^{-b\lambda}\Big(\int_{\bar{a}-\sigma_a}^{\tilde{a}_{21}} \big[f - (\pi_2^{per,adj}(a_2) - \kappa) \big] \frac{1}{2\sigma_a} da_2 + \int_{\bar{a}-\sigma_a}^{\underline{a}_2} \big[\pi_2^{per,adj}(a_2) - \pi_2^{per,no}(a_2) - \kappa \big] \frac{1}{2\sigma_a} da_2$$
$$+ \int_{\bar{a}_2}^{\bar{a}+\sigma_a} \big[\pi_2^{per,adj}(a_2) - \pi_2^{per,no}(a_2) - \kappa \big] \frac{1}{2\sigma_a} da_2 \Big) - c_1 = 0,$$

After substituting the expression of $\pi_2^{per,adj}(a_2) - \pi_2^{per,no}(a_2)$ and various cutoffs into the above equation, we can rewrite the above expression as

$$be^{-b\lambda}\Big(\int_{\bar{a}-\sigma_a}^{\tilde{a}_{21}} \Big[(f+\kappa) - \frac{(a_2 + \tau - \gamma c_0)^2}{4\gamma} \Big] \frac{1}{2\sigma_a} da_2 \Big)$$
$$be^{-b\lambda}\Big(\int_{\bar{a}-\sigma_a}^{\bar{a}-2\sqrt{\gamma\kappa}} \big[(a_2 - \bar{a})^2 - \kappa \big] \frac{1}{2\sigma_a} da_2 + \int_{\bar{a}+2\sqrt{\gamma\kappa}}^{\bar{a}+\sigma_a} \big[(a_2 - \bar{a})^2 - \kappa \big] \frac{1}{2\sigma_a} da_2 \Big) - c_1 = 0, \tag{23}$$

It is straightforward to observe that the second and third terms above are not affected by the change in the mean of the demand shifter. In addition, we show that the first term decreases when $\bar{a}$ increases in Appendix 5.1.4. Next, when $\bar{a} + 2\sqrt{\gamma\kappa} > 2\sqrt{\gamma(f+\kappa)} + \gamma c_0 - \tau \geq \bar{a} - 2\sqrt{\gamma\kappa}$, we can write the benefit of acquiring information minus the cost of acquiring information as

$$L(\lambda, \bar{a}) \equiv (1 - e^{-b\lambda})\Big(\int_{\bar{a}-\sigma_a}^{\tilde{a}_{22}} \big[f - \pi_2^{per,no}(a_2) \big] \frac{1}{2\sigma_a} da_2 + \int_{\bar{a}_2}^{\bar{a}+\sigma_a} \big[\pi_2^{per,adj}(a_2) - \pi_2^{per,no}(a_2) - \kappa \big] \frac{1}{2\sigma_a} da_2 \Big) - c_1\lambda. \tag{24}$$

The optimal choice of λ by

$$be^{-b\lambda}\Big(\int_{\bar{a}-\sigma_a}^{\tilde{a}_{22}}(f-\pi_2^{per,no}(a_2))\frac{1}{2\sigma_a}da_2\Big)+be^{-b\lambda}\Big(+\int_{\bar{a}+2\sqrt{\gamma\kappa}}^{\bar{a}+\sigma_a}\left[(a_2-\bar{a})^2-\kappa\right]\frac{1}{2\sigma_a}da_2\Big)-c_1=0. \quad (25)$$

In Appendix 5.1.4, we also prove that the marginal benefit of acquiring information decreases in $\bar{a}$. In total, the marginal benefit of acquiring information increases in both cases, when there is a negative first moment to the distribution of the demand shifter.

From equations (23) and (25), we see that the marginal benefit of acquiring information comes from two parts in both cases: the part that increases the profit as the firm switches from fixing the price to adjusting the price[28] and the part that increases the profit as the firm switches from producing[29] to not producing (which yields a zero profit). The first part is unaffected by a change in $\bar{a}$, as the two cutoffs for the price adjustment move proportionately (and in the same direction) with $\bar{a}$ and the profit difference between fixing and adjusting the price only depends on the difference between $\bar{a}$ and the realized demand shifter.

There are one or two effects on the second part, when $\bar{a}$ decreases marginally. First, as the lower bound $\bar{a}-\sigma_a$ decreases when $\bar{a}$ goes down, the likelihood of stopping production increases and the firm saves (marginally) more on receiving a negative profit (as the firm with $a_2=\bar{a}-\sigma_a$ gains strictly by not producing).[30] Second, note that the zero-profit threshold ($\tilde{a}_{21}$) does not change in the first case, when $\bar{a}$ goes down. Therefore, the marginal benefit of acquiring information goes up in the first case unambiguously, when $\bar{a}$ goes down. Third, although the zero-profit threshold, $\tilde{a}_{22}$, may change in the second case, the marginal effect triggered by this possible change is zero as firms with $a_2=\tilde{a}_{22}$ is indifferent between not producing and producing with a fixed price in the second case (i.e., $f-\pi_2^{per,no}(\tilde{a}_{22})=0$). Therefore, the marginal benefit of acquiring information goes up unambiguously in the second case as well. In total, the marginal benefit of acquiring information increases in both cases after a negative first moment shock to the distribution of the demand shifter.

3.4.3 Price Stickiness

Based on the results derived above, we have the following proposition concerning how a first moment shocks affects information acquisition and price stickiness.

Proposition 4 *A decrease in the mean of demand shifter leads to three results. First, the*

[28] Specifically, they are the last two terms of equation (23) and the last term of equation (25).

[29] Specifically, the firm either adjusts the price as in the first term of equation (23) or fixes the price as in the first term of equation (25).

[30] Here, I mean $f-\pi_2^{per,no}(\bar{a}-\sigma_a)>0$ and $f-(\pi_2^{per,adj}(\bar{a}-\sigma_a)-\kappa)>0$, as $\bar{a}-\sigma_a<\tilde{a}_2\equiv\min(\tilde{a}_{22},\tilde{a}_{21})$.

intensity of information acquisition goes up. As a result, the firm updates its demand/sales expectations more frequently. Second, conditional on an update in demand/sales expectations, the likelihood of changing the output price either decreases (in the first case) or stays unchanged (in the second case). Finally, the overall probability of price adjustment either changes ambiguously (in the first case) or increases (in the second case).

Proof. See Appendix 5.1.5. ■

We believe that the first case considered above is empirically more plausible. In the second case, there are no firms that reduce prices from the first period to the second period, as those firms that reduce prices in our benchmark model stop production now. As there are non-negligible amounts of firms that reduce prices from last quarter to the current quarter in our data, the first case which has firms that reduce prices is empirically more relevant.

We believe that the shock that can explain all our four stylized facts is more likely to the second moment shock rather than the first moment shock. Apart from not being able to generate a counter-cyclical volatility of firm sales in our simple model, the first moment shock misses one key stylized fact that conditional on an update in demand/sales expectations, the likelihood of changing the price increases when the GDP growth rate goes down. As we have shown in the above proposition, the first moment shock *cannot* yield this prediction even if it can yield the result that the *overall* probability of price adjustment increases when the GDP growth rate goes down. The bottom line is that a first moment shock incentivizes the firm to acquire more information, but does not increase the sensitivity of the price adjustment with respect to a belief update in the firm's demand conditions.

The final remark (and caveat) we want to make is that all our analysis concerns comparing firms' pricing and information acquisition strategies between two steady states. They can be two steady states with different variances of the demand shifter and/or with different means of the demand shifter. Our model is completely silent on how the firms adjust their prices and information acquisition intensity on the *transitional path* from a regime with a lower level of uncertainty (or mean) to a regime with a higher level of uncertainty (or mean). In a full-fledged stochastic general equilibrium model with recurring aggregate shocks, we are able to finish all these tasks.

4 Conclusions

Using a unique quarterly panel dataset that contains information on firm expectations and price adjustments, we examine the relationship between information acquisiton and price adjustments. We find that firms experienced the changes in input cost or demand tend to adjust their prices but the effects of changes in cost and demand on price adjustments are small and firms' price adjustments donot repspond immediatedly to the changes in cost and demand. Compared with the changes in demand, the changes in input cost have a larger impact on price adjustments. Moreover, we show that a firm's expectation updating is positively correlated with its price adjustments and the price stickness and information rigidity increase in upturns and decrease in downturns. This implies that firms update expectations and adjust their prices more frequently in downturns than in upturns, making the monetary policy less effective in recessions.

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5 Appendix

5.1 Proofs

5.1.1 Proof for Proposition 1

First, if the demand shifter is not observed in the second period, the firm does not adjust the price (i.e., $p_2 = p_1$) as the firm uses the prior to form its expectation for the demand. As a result, the realized profit is

$$\pi_2^{imper}(a_2) = \pi_2^{per,no}(a_2) = \frac{1}{4\gamma}\Big[(\bar{a} + \tau - \gamma c_0)(2a_2 - \bar{a} + \tau - \gamma c_0)\Big]. \tag{26}$$

In such a case, the firm integrates a_2 uniformly in the interval of $[\bar{a} - \sigma_a, \bar{a} + \sigma_a]$ to derive the expected profit in the second period.

Next, by comparing equations (12) with (13), we find that the benefit of adjusting the output price increases with the deviation of the second-period's demand shifter from the prior mean while the cost of adjusting the output price is fixed. Therefore, the condition in equation (14) pins down the "Ss" pricing policy.

Finally, $\frac{\bar{a}+\tau}{2\gamma} + \frac{c_0}{2}$ is the optimal price in the first period, as it maximizes the static profit in the first period and the expected profit in the second period when the firm does not observe its true demand shifter.

5.1.2 Proof for Proposition 2

First, calculation shows that

$$\begin{aligned}
& \sigma_a \frac{\partial^2 L(\lambda, \sigma_a)}{\partial \sigma_a \partial \lambda} \\
= \; & be^{-b\lambda}\Big(\frac{1}{2}\big[\pi_2^{per,adj}(\bar{a} - \sigma_a) - \pi_2^{per,no}(\bar{a} - \sigma_a) - \kappa\big] \\
& - \int_{\bar{a}-\sigma_a}^{\underline{a}_2} \big[\pi_2^{per,adj}(a_2) - \pi_2^{per,no}(a_2) - \kappa\big]\frac{1}{2\sigma_a} da_2\Big) \\
& + be^{-b\lambda}\Big(\frac{1}{2}\big[\pi_2^{per,adj}(\bar{a} + \sigma_a) - \pi_2^{per,no}(\bar{a} + \sigma_a) - \kappa\big] \\
& - \int_{\bar{a}_2}^{\bar{a}+\sigma_a} \big[\pi_2^{per,adj}(a_2) - \pi_2^{per,no}(a_2) - \kappa\big]\frac{1}{2\sigma_a} da_2\Big) > 0,
\end{aligned}$$

as $\underline{a}_2 < \bar{a} < \bar{a}_2$ and $\pi_2^{per,adj}(a_2) - \pi_2^{per,no}(a_2) - \kappa$ decreases from $\bar{a} - \sigma_a$ to $\bar{a}$ and increases from $\bar{a}$ to $\bar{a} + \sigma_a$.

The first result of the proposition is true, as

$$\frac{\partial^2 L(\lambda, \sigma_a)}{\partial \sigma_a \partial \lambda} > 0.$$

As the firm acquires information at a higher intensity, the firm updates its demand/sales expectation with a higher probability. Second, conditional on an update in demand/sales expectation, (i.e., the demand shifter of a_2 is observed), the probability of adjusting the price is

$$\frac{2\sigma_a - (\overline{a}_2 - \underline{a}_2)}{2\sigma_a}.$$

As both $\underline{a}_2$ and $\overline{a}_2$ do not depend on σ_a, the probability of adjusting the price increases with the variance of the demand shifter. Finally, the overall probability of price adjustments equals

$$(1 - e^{-b\lambda^*(\sigma_a)})\frac{2\sigma_a - (\overline{a}_2 - \underline{a}_2)}{2\sigma_a}.$$

As both $\lambda^*(\sigma_a)$ and σ_a go up, the overall probability of changing the price increases.

5.1.3 Proof for Proposition 3

First, equation (21) implies that

$$\tilde{a}_{22} = \frac{1}{2}\Big[\Big(\frac{4\gamma f}{\bar{a} + \tau - \gamma c_0}\Big) + (\bar{a} - \tau + \gamma c_0)\Big] < \frac{1}{2}(\bar{a} + \tau - \gamma c_0 + \bar{a} - \tau + \gamma c_0) = \bar{a},$$

which is true under Assumption 4. Thus, it must be true that

$$\tilde{a}_{22} < \overline{a}_2.$$

Therefore, we have two cases to consider in total.

We discuss the first case here. When $2\sqrt{\gamma(f + \kappa)} + \gamma c_0 - \tau < \bar{a} - 2\sqrt{\gamma\kappa}$, we have $\tilde{a}_2 = \tilde{a}_{21} < \underline{a}_2$. We have four possibilities in total. First, for firms with $a_2 \in (\overline{a}_2, \bar{a} + \sigma_a]$, changing the price dominates fixing the price (as $a_2 > \overline{a}_2$) and stopping producing (as $a_2 > \tilde{a}_2$). As a result, firms increase the price from $\frac{\bar{a}+\tau}{2\gamma} + \frac{c_0}{2}$ to $\frac{a_2+\tau}{2\gamma} + \frac{c_0}{2}$ and stay. Second, for firms with $a_2 \in [\underline{a}_2, \overline{a}_2]$, fixing the price dominates changing the price (as $a_2 \leq \overline{a}_2$) and stopping producing (as $a_2 > \tilde{a}_2$). Thus, firms fix the price at $\frac{\bar{a}+\tau}{2\gamma} + \frac{c_0}{2}$ and stay. Third, for firms with $a_2 \in [\tilde{a}_2, \underline{a}_2)$, changing the price dominates fixing the price (as $a_2 < \underline{a}_2$) and stopping producing (as $a_2 > \tilde{a}_2$) again. Finally, for firms with $a_2 \in [\bar{a} - \sigma_a, \tilde{a}_2]$, stopping producing dominates fixing the price (as $a_2 \leq \tilde{a}_2 \leq \underline{a}_2$) and changing the price (as $a_2 \leq \tilde{a}_2$). Therefore, firms stop producing and earn zero profit.

Now, we discuss the second case. When $\bar{a}+2\sqrt{\gamma\kappa} > 2\sqrt{\gamma(f+\kappa)}+\gamma c_0-\tau \geq \bar{a}-2\sqrt{\gamma\kappa}$, we have three types of firms. First, for firms with $a_2 \in (\overline{a}_2, \bar{a}+\sigma_a]$, changing the price dominates fixing the price (as $a_2 > \overline{a}_2$) and stopping producing (as $a_2 > \tilde{a}_{21}$). Second, for firms with $a_2 \in [\bar{a}-\sigma_a, \underline{a}_2)$, stopping producing dominates changing the price as $a_2 < \tilde{a}_{21}$ and changing the price yields a higher payoff than fixing the price as $a_2 < \underline{a}_2$. Thus, stopping producing is optimal for this type of firms. Finally, for firms with $a_2 \in [\underline{a}_2, \overline{a}_2]$, we first prove that $\tilde{a}_{22}$ must be bigger than or equal to $\underline{a}_2$. Suppose it is not. Then, we would have an interval of $[\tilde{a}_{22}, \underline{a}_2)$. For firms with a_2 within this interval, fixing the price is dominated by adjusting the price (as $a_2 < \underline{a}_2$) and stopping producing is dominated by fixing the price (as $a_2 \geq \tilde{a}_{22}$). Thus, firms prefer adjusting the price instead of not producing. However, as we are in the case in which $2\sqrt{\gamma(f+\kappa)}+\gamma c_0-\tau \geq \bar{a}-2\sqrt{\gamma\kappa}$ (i.e., $\tilde{a}_{21} \geq \underline{a}_2$), not producing dominates adjusting the price as $a_2 < \tilde{a}_{21}$ (a contradiction). Therefore, we must have $\tilde{a}_{22} \geq \underline{a}_2$. Accordingly, for firms with $a_2 \in [\underline{a}_2, \tilde{a}_{22}]$, not producing dominates fixing the price which dominates adjusting the price. For firms with $a_2 \in [\tilde{a}_{22}, \overline{a}_2]$, fixing the price dominates adjusting the price and not producing. In total, we have three types of firms: (1) for firms with $a_2 \in (\overline{a}_2, \bar{a}+\sigma_a]$, the price increases from $\frac{\bar{a}+\tau}{2\gamma}+\frac{c_0}{2}$ to $\frac{a_2+\tau}{2\gamma}+\frac{c_0}{2}$; (2) for firms with $a_2 \in [\tilde{a}_{22}, \overline{a}_2]$, the price is unchanged; (3) for firms with $a_2 \in [\bar{a}-\sigma_a, \tilde{a}_{22})$, they choose to not produce

Finally, we show that it cannot be true that $2\sqrt{\gamma(f+\kappa)}+\gamma c_0-\tau \geq \bar{a}+2\sqrt{\gamma\kappa}$ (i.e., $\tilde{a}_{21} \geq \overline{a}_2$). We prove it by contradiction. Suppose $\tilde{a}_{21} \geq \overline{a}_2$ and the firm's demand shifter $a_2 \in [\overline{a}_2, \tilde{a}_{21}]$. Then, the firm prefers adjusting the price over fixing the price as $a_2 \geq \overline{a}_2$ and not producing over adjusting the price as $a_2 \leq \tilde{a}_{21}$. Thus, the firm prefers not producing over fixing the price. However, we have shown that the cutoff (i.e., $\tilde{a}_{22}$) above which the firm prefers fixing the price over not producing must be strictly below $\bar{a}$ and accordingly $\overline{a}_2$ which is bigger than $\bar{a}$. Thus, we have a contradiction. Therefore, it has to be the case that $\tilde{a}_{21} < \overline{a}_2$

5.1.4 Marginal Benefit of Acquiring Information and Endogenous Exiting

We prove that the marginal benefit of acquiring information in the case with a fixed operation cost decreases with the mean of the demand shifter, $\bar{a}$. For the case in which $\bar{a}-2\sqrt{\gamma\kappa} > 2\sqrt{\gamma(f+\kappa)}+\gamma c_0-\tau$, we only need to prove that

$$Z(\bar{a}) \equiv \Big(\int_{\bar{a}-\sigma_a}^{\tilde{a}_{21}} \left[(f+\kappa) - \frac{(a_2+\tau-\gamma c_0)^2}{4\gamma} \right] \frac{1}{2\sigma_a} da_2 \Big)$$

decreases with $\bar{a}$. Taking the first order derivative of the above expression with respect to $\bar{a}$, we end up with

$$2\sigma_a \frac{dZ(\bar{a})}{d\bar{a}} = -\left[(f+\kappa) - \frac{(\bar{a} - \sigma_a + \tau - \gamma c_0)^2}{4\gamma} \right] < 0,$$

as

$$(f+\kappa) - \frac{(\tilde{a}_{21} + \tau - \gamma c_0)^2}{4\gamma} = 0.$$

For the case in which $\bar{a} + 2\sqrt{\gamma\kappa} > 2\sqrt{\gamma(f+\kappa)} + \gamma c_0 - \tau \geq \bar{a} - 2\sqrt{\gamma\kappa}$, the marginal benefit of acquiring information equals

$$be^{-b\lambda}\Big(\int_{\bar{a}-\sigma_a}^{\tilde{a}_{22}} (f - \pi_2^{per,no}(a_2)) \frac{1}{2\sigma_a} da_2 \Big) + be^{-b\lambda}\Big(+ \int_{\bar{a}+2\sqrt{\gamma\kappa}}^{\bar{a}+\sigma_a} \big[(a_2 - \bar{a})^2 - \kappa\big] \frac{1}{2\sigma_a} da_2 \Big)$$

First, note that the second part of the term above is unaffected by $\bar{a}$. Next, the first order derivative of the first part with respect to $\bar{a}$ is

$$-\big[f - \pi_2^{per,no}(\bar{a} - \sigma_a)\big] < 0,$$

as

$$f - \pi_2^{per,no}(\tilde{a}_{22}) = 0.$$

In total, the marginal benefit of acquiring information decreases with an increase in the mean of the demand shifter, $\bar{a}$, in both cases.

5.1.5 Proof for Proposition 4

The first result of the proposition is true, as have shown that

$$\frac{\partial^2 L(\lambda, \bar{a})}{\partial \bar{a} \partial \lambda} < 0,$$

which leads to the result that

$$\frac{d\lambda^*(\bar{a})}{d\bar{a}} < 0,$$

where $\lambda^*(\bar{a})$ is the optimal intensity of acquiring information which depends on the mean of the demand shifter. Moreover, as the firm acquires information at a higher intensity, the firm updates its demand/sales expectation with a higher probability.

Second, conditional on an update in demand/sales expectation, (i.e., the demand shifter of

a_2 is observed), the probability of adjusting the price (an increase or a decrease) is

$$\frac{(\sigma_a + \bar{a} - \overline{a}_2) + (\underline{a}_2 - \tilde{a}_{21})}{2\sigma_a} = \frac{\sigma_a - 2\sqrt{\gamma\kappa}}{2\sigma_a} + \frac{\bar{a} - 2\sqrt{\gamma\kappa} - (2\sqrt{\gamma(f+\kappa)} + \gamma c_0 - \tau)}{2\sigma_a}$$

in the first case and

$$\frac{\sigma_a + \bar{a} - \overline{a}_2}{2\sigma_a} = \frac{\sigma_a - 2\sqrt{\gamma\kappa}}{2\sigma_a}$$

in the second case. It is straightforward to observe that the first probability decreases when $\bar{a}$ goes down and the second is unchanged when $\bar{a}$ decreases.

Finally, the overall probability of adjusting the price is the probability of knowing the demand shifter in the second period multiplied by the probability of adjusting the price conditioning on an update in demand/sales expectation. The probability of knowing the demand shifter in the second period increase when $\bar{a}$ goes down, as the firm increases the intensity of acquiring information. The probability of adjusting the price conditioning on an update in demand/sales expectation decreases (in the first case) or stays unchanged (in the second case) when $\bar{a}$ goes down. Therefore,the overall probability of changing the price either changes ambiguously (in the first case) or increases (in the second case).

5.2 Tables

Table 12: Updating in sales forecast and GDP growth

	(1)	(2)	(3)	(4)	(5)	(6)
Dep.Var:	Indicator for sales forecast last quarter $\neq$ sales forecast this quarter					
gr prev qr	-0.378***	-0.379***				
	(0.069)	(0.069)				
lagged log size		-0.008***	-0.006**		-0.008***	-0.006*
		(0.003)	(0.003)		(0.003)	(0.003)
lagged log size X gr prev qr			0.188***			
			(0.040)			
gr last qr				-0.462***	-0.463***	
				(0.033)	(0.033)	
lagged log size X gr last qr						-0.072***
						(0.020)
constant	0.723***	0.770***	0.759***	0.725***	0.773***	0.759***
	(0.000)	(0.018)	(0.018)	(0.000)	(0.018)	(0.018)
Industry FE	Yes	Yes	No	Yes	Yes	No
Region FE	Yes	Yes	No	Yes	Yes	No
Industry-quarter FE	No	No	Yes	No	No	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Region-quarter FE	No	No	Yes	No	No	Yes
N	364685	364685	364673	364685	364685	364673
R^2	0.279	0.279	0.308	0.279	0.279	0.308

* 0.10 ** 0.05 *** 0.01. Standard errors are clustered at the firm level, and all regressions include firm fixed effects. The indicator for an update in sales forecast is defined in a strict sense. We regress the indicator of updating sales forecast on GDP growth, firm size (lagged registered capital) and their interaction term. gr prev qr is the lagged quarterly growth rate compared to the previous quarter. gr last qr is the lagged quarterly growth rate compared to the same quarter of last year.

Table 13: Serial correlation of forecast errors and GDP growth rate (domestic data): using residual forecast errors

	(1)	(2)	(3)	(4)
Dep.Var:	$\hat{\epsilon}_{FE^{log}}$		$\hat{\epsilon}_{FE^{pct}}$	
lagged $\hat{\epsilon}_{FE^{log}}$	0.164***	0.165***		
	(0.007)	(0.007)		
lagged $\hat{\epsilon}_{FE^{log}}$ X gr last semi	0.815***			
	(0.231)			
lagged $\hat{\epsilon}_{FE^{log}}$ X gr prev semi		2.648***		
		(0.507)		
lagged $\hat{\epsilon}_{FE^{pct}}$			0.160***	0.159***
			(0.007)	(0.007)
lagged $\hat{\epsilon}_{FE^{pct}}$ X gr last semi			0.476*	
			(0.262)	
lagged $\hat{\epsilon}_{FE^{pct}}$ X gr prev semi				2.678***
				(0.594)
constant	-0.000	-0.001	-0.001*	-0.001**
	(0.000)	(0.000)	(0.001)	(0.001)
Industry-quarter FE	Yes	Yes	Yes	Yes
Region-quarter FE	Yes	Yes	Yes	Yes
N	94620	94620	94716	94716
R^2	0.074	0.075	0.069	0.069

* 0.10 ** 0.05 *** 0.01. Standard errors are clustered at the firm level. We regress the forecast error on the lagged forecast error and its interaction term with the semi-year GDP growth rate. Top and bottom one percent of forecast errors are trimmed. gr prev semi is the lagged semi-year growth rate compared to the previous semi-year. gr last semi is the lagged semi-year growth rate compared to the same semi-year of last year. $\hat{\epsilon}_{FE^{log}}$ is the residual log forecast error, which we obtain by regressing FE^{log} on a set of region-year, country-year and size-year fixed effects. Similarly, $\hat{\epsilon}_{FE^{pct}}$ is the residual percentage forecast error, which we obtain by regressing FE^{pct} on a set of industry-year, region-year and size-year fixed effects. All regressions control for industry-quarter and region-quarter fixed effects. This regression is at the semi-year frequency, and forecasts made in the second quarter and the fourth quarter are used.

Table 14: Serial correlation of forecast errors and GDP growth rate (domestic data): survivors only

	(1)	(2)	(3)	(4)
Dep.Var:	FE^{log}		FE^{pct}	
lagged FE^{log}	0.205***	0.203***		
	(0.008)	(0.008)		
lagged FE^{log} X gr prev semi	3.373***			
	(0.522)			
lagged FE^{log} X gr last semi		1.427***		
		(0.242)		
lagged FE^{pct}			0.198***	0.197***
			(0.009)	(0.009)
lagged FE^{pct} X gr prev semi			3.319***	
			(0.613)	
lagged FE^{pct} X gr last semi				1.059***
				(0.276)
constant	-0.011***	-0.011***	-0.006***	-0.006***
	(0.001)	(0.001)	(0.001)	(0.001)
Industry-quarter FE	Yes	Yes	Yes	Yes
Region-quarter FE	Yes	Yes	Yes	Yes
N	69649	69649	69698	69698
R^2	0.168	0.168	0.154	0.154

* 0.10 ** 0.05 *** 0.01. Standard errors are at the firm level. We only utilize surviving firms in this regression. I.e., firms that have appeared in the dataset for at least eight consecutive quarters (i.e., two year). We regress the forecast error on the lagged forecast error and its interaction term with the semi-year GDP growth rate. Top and bottom one percent of forecast errors are trimmed. gr prev semi is the lagged semi-year growth rate compared to the previous semi-year. gr last semi is the lagged semi-year growth rate compared to the same semi-year of last year. FE^{log} is the log deviation of the realized sales from the projected sales, while FE^{pct} is the percentage deviation of the realized sales from the projected sales. All regressions control for industry-quarter and region-quarter fixed effects. This regression is at the semi-year frequency, and forecasts made in the second quarter and the fourth quarter are used.

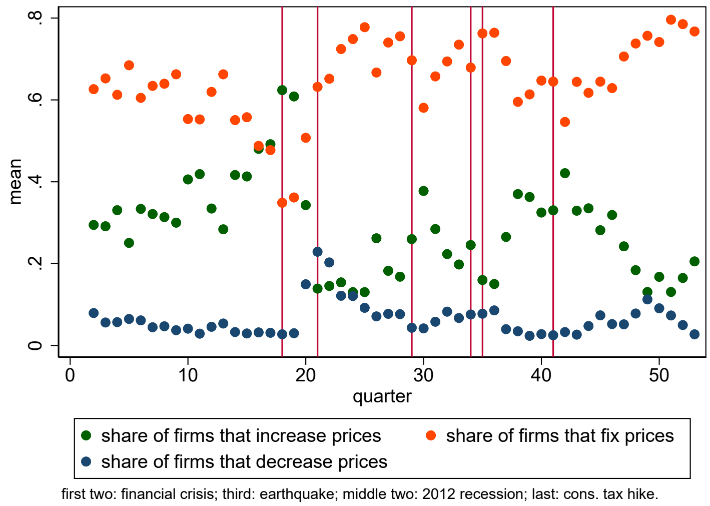
Table 15: Sensitivity of output price change to firm-specific demand change and economic fluctuation

	(1)	(2)	(3)	(4)	(5)	(6)
Dep.Var:	Indicator (output price (t) $\neq$ output price (t-1))					
firm demand(t) $\neq$ firm demand(t-1)	0.163***	0.166***	0.163***	0.166***	0.157***	0.160***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
gr prev qr	-0.895***		-0.895***			
	(0.059)		(0.059)			
firm demand(t) $\neq$ firm demand(t-1) X gr prev qr	-0.612***		-0.612***		-0.344***	
	(0.100)		(0.100)		(0.124)	
gr last qr		-0.364***		-0.364***		
		(0.034)		(0.034)		
firm demand(t) $\neq$ firm demand(t-1) X gr last qr		-0.565***		-0.565***		-0.582***
		(0.061)		(0.061)		(0.065)
lagged log firm size			0.000	0.000	-0.003	-0.003
			(0.003)	(0.003)	(0.003)	(0.003)
constant	0.177***	0.179***	0.175***	0.177***	0.195***	0.195***
	(0.001)	(0.001)	(0.020)	(0.020)	(0.019)	(0.019)
Industry FE	Yes	Yes	Yes	Yes	No	No
Region FE	Yes	Yes	Yes	Yes	No	No
Industry-quarter FE	No	No	No	No	Yes	Yes
Region-quarter FE	No	No	No	No	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
N	384912	384912	384912	384912	384896	384896
R^2	0.436	0.436	0.436	0.436	0.454	0.454

* 0.10 ** 0.05 *** 0.01. Standard errors are clustered at the firm level, and all regressions include firm fixed effects. We regress the indicator of adjusting output price on the indicator of changing firm-specific demand, the lagged quarterly GDP growth rate, and their interaction term. gr prev qr is the lagged quarterly growth rate compared to the previous quarter. gr last qr is the lagged quarterly growth rate compared to the same quarter of last year.

5.3 Figures

Figure 5: Time-series plot of input price adjustments



Note: This figure plots how the fraction of firms that fix or increase or decrease their input prices (from last quarter to current quarter) evolves over time.