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Abstract

Does time-varying business volatility affect the price setting of firms and thus the transmission of monetary policy into the real economy? To address this question, we estimate from the firm-level micro data of the German IFO Business Climate Survey the impact of idiosyncratic volatility on the price setting behavior of firms. In a second step, we use a calibrated New Keynesian business cycle model to gauge the effects of time-varying volatility on the transmission of monetary policy to output. Our results are twofold. Heightened business volatility increases the probability of a price change, though the effect is small: the tripling of volatility during the recession of 08/09 caused the average quarterly likelihood of a price change to increase from 31.6% to 32.3%. Second, the effects of this increase in volatility on monetary policy are also small; the initial effect of a 25 basis point monetary policy shock to output declines from 0.347% to 0.341%.

JEL-Classification: E30, E31, E32, E50

Keywords: survey data, time-varying volatility, price setting, New Keynesian model, monetary policy

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1 Introduction

Does time-varying business volatility affect the price setting of firms and thus the real effects of monetary policy? A fundamental result of New Keynesian macroeconomics is that, due to price stickiness, changes in monetary policy affect real variables in the short run. If heightened volatility or uncertainty were to change the degree of price rigidity, this would directly influence monetary policy transmission. This channel is potentially important as price flexibility seems to be countercyclical in the data. This is shown by Vavra (2013) for U.S. consumer price data, and we confirm this finding with producer price data from the West German manufacturing sector. This means that prices seem to become more flexible and, possibly, monetary policy less effective in times when monetary stabilization is perhaps most needed.

Against this backdrop the contribution of this paper is threefold. We construct firm-specific expectation errors from the micro data of the West German manufacturing part of the IFO survey and use their absolute values as well as rolling-window standard deviations as proxies for idiosyncratic business volatility. Second, we demonstrate that idiosyncratic firm-level volatility is a statistically significant, albeit economically somewhat modest determinant in the price setting behavior of firms. Third, we show in a New Keynesian dynamic stochastic general equilibrium (DSGE) model that monetary policy has smaller real effects in highly volatile times. We also show that this effect on monetary policy transmission is quantitatively small.

Since the beginning of the financial crisis, there has been a renewed interest in the consequences of volatility/uncertainty for economic activity starting with the seminal paper by Bloom (2009). This growing literature mostly deals with the interaction of uncertainty and investment decisions of firms, where the propagation mechanisms discussed are physical adjustment frictions (e.g., Bloom, 2009; Bachmann and Bayer, forthcoming; Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry, 2012), financial frictions (e.g., Christiano, Motto, and Rostagno, 2010; Gilchrist, Sim, and Zakrajsek, 2010; Arellano, Bai, and Kehoe, 2012), or agency problems within production units (e.g., Narita, 2011; Panousi and Papanikolaou, 2012).

The consequences of heightened volatility for the price-setting decisions of firms, however, have remained largely unexplored. In a recent contribution, Vavra (2013) matches an Ss price-setting model to CPI micro data and shows that idiosyncratic volatility affects the level of price rigidity and, through it, leads to time-varying effects of monetary policy.[1] Theoretically, heightened business volatility can have two effects. First, to the extend that volatility also constitutes uncertainty for firms and adjusting prices is subject to some degree of irreversibility, firms may want to "wait and see", refrain from adjusting their prices and, thus, prices become endogenously more sticky. Second, higher volatility makes price adjustment of firms more likely as firms are hit by larger shocks. Hence, the sign of the relationship between firm-level volatility and likelihood of price adjustment is an empirical question. Vavra (2013) analyzes the importance of both effects and shows that in his calibration the volatility effect dominates. Heightened volatility would therefore trigger an increase in the frequency of price adjustment and would make monetary policy less effective.

The novel contribution of this paper is to compute measures of firm-specific volatility and to estimate and quantify directly the impact of heightened firm-level volatility on the firms' price setting behavior.

[1] The focus on idiosyncratic (i.e., firm-specific) rather than aggregate volatility is justified as Boivin, Giannoni, and Mihov (2009), Golosov and Lucas (2007) as well as Klenow and Kryvtsov (2008) show that idiosyncratic shocks are the most important factor in explaining price dynamics at the micro-level.

These business volatility measures are constructed from the confidential micro data in the IFO Business Climate Survey (IFO-BCS). Survey micro data are well-suited for our research question as they are based on statements from actual decision-makers at the firms as opposed to, for example, outside analysts. This means that our measures of business volatility will also capture uncertainty at the firm level and thus allow the "wait-and-see" effect caused by uncertainty to shine through. Survey data are also less likely to suffer from strategic behavior, such as, e.g., public earnings announcements, as they are highly confidential and can only be accessed under strict non-disclosure agreements. The unique feature of the German IFO-BCS is that it allows us to construct firm-specific volatility measures and that it contains information on the price setting behavior of the same firms.

We use two strategies to construct the firm-specific volatility measures. The first one follows Bachmann, Elstner, and Sims (2013) and Bachmann and Elstner (2013). Bachmann et al. (2013) construct expectation errors at the firm level, based on qualitative survey questions. We use the absolute value of these expectation errors as one of our measures for instantaneous idiosyncratic volatility. The advantage of this qualitative measure is that it can be constructed for a relatively large sample of firms. However, they only allow us to evaluate the sign of the relationship between volatility and price setting at the firm-level. Therefore, we compute for a subset of firms a quantitative volatility measure in line with Bachmann and Elstner (2013) from firm statements about capacity utilization. With this quantitative volatility measure we then assess the magnitude of the effect of idiosyncratic volatility on the price setting behavior of firms and use this elasticity as an input into a fully calibrated structural model.

The second strategy is based on the same qualitative and quantitative expectation errors but, instead of the absolute expectation error, uses a firm-specific rolling window standard deviation as in Comin and Mulani (2006) and Davis, Haltiwanger, Jarmin, and Miranda (2006). We show that volatility measures based on either procedure are highly correlated and that our substantive results are robust across these different specifications.

In order to assess to what extent heightened firm-level volatility affects the frequency of price adjustment, we estimate a probit model on a panel of (on average) 2,500 German firms from January 1980 to December 2011. Our results confirm that heightened volatility increases the frequency of price changes. For example, the tripling of volatility during the recession of 08/09 – an increase of about 6 standard deviations – caused the average quarterly likelihood of a price change to increase from 31.6% to 32.3%. This means that indeed the volatility dominates the pure uncertainty effect empirically.

After having established the link between price setting and idiosyncratic volatility in our survey data, we use an off-the-shelve New Keynesian DSGE model (see, e.g., Galí, 2008), where price setting is constrained à la Calvo (1983), to flesh out the impact of heightened volatility on the effectiveness of monetary policy. It is well known that, due to the absence of selection effects (see, e.g., Golosov and Lucas, 2007), the Calvo model generates a larger degree of monetary non-neutrality compared to a menu cost model, making it a natural, conservative choice for our exercise. Using the uncovered empirical relationship between an increase in firm-specific volatility and the probability of a price change, we then capture a change in firm-specific volatility through a change in the Calvo parameter.

Our results show that, even though idiosyncratic volatility was at the trough of the 08/09-recession roughly three times higher than on average before, the resulting effect on the frequency of price adjustment is small. During this time, a monetary stimulus of a 25 basis point cut in the nominal interest rate, would have lost about 1.6 percent of its effect on real output, with the impact effect decreasing from 0.347% to

0.341%. However, while heightened business volatility in isolation would not have led to a large increase in price flexibility in the 08/09-recession, we observe an overall increase in the average share of firms adjusting their price by about 7 percentage points in the same time period. Such a sizable increase in price flexibility would have translated into a decline in the output impact effect of a 25 basis point monetary policy shock from 0.346% to 0.289%, a decrease of almost 17 percent. Hence, while changes in price flexibility over the business cycle are potentially an important issue for the conduct of monetary policy, they are unlikely to be driven by changes in firm-level volatility.

The remainder of this paper is structured as follows. The next section describes the IFO-BCS and the construction of the business volatility measures from it. In Section 3 we introduce the microeconometric framework and present the effects of changes in volatility on the price setting of firms. Section 4 outlines the New Keynesian DSGE model and discusses the baseline results. We provide robustness checks in Section 5. The last section concludes.

2 Measuring Idiosyncratic Volatility

In this section we describe the construction of idiosyncratic volatility measures from IFO Business Climate Survey (IFO-BCS) data.

2.1 IFO Business Climate Survey

The IFO Business Climate index is a much-followed leading indicator for economic activity in Germany. It is based on a firm survey which has been conducted since 1949 (see Becker and Wohlrabe, 2008, for details). Since then the survey design of the IFO Business Climate index has been adopted by other surveys such as the Confederation of British Industry for the UK manufacturing sector or the Tankan survey for Japanese firms. Due to longitudinal consistency problems in other sectors and the unavailability of micro data in a processable form before 1980 we limit our analysis to the manufacturing sector from 1980 until 2011. Our analysis excludes East German firms.

An attractive feature of the IFO-BCS is the high number of participants. The average number of respondents at the beginning of our sample is approximately 5,000; towards the end the number is about half that at 2,300.[2] Participation in the survey is voluntary and there is some fraction of firms that are only one-time participants. However, conditional on staying two months in the survey, most firms continue to participate each month. In terms of firm size, about 9.4% of firms in our sample have less than 20 employees, roughly 32.0% have more than 20 but less than 100 employees, 47.3% employed between 100 and 1000 people, and 11.3% have a workforce of more than 1000.

The IFO-BCS, in its core, is a monthly qualitative business survey where firms provide answers that fall into three qualitative categories: *Increase*, *Decrease*, and a neutral category. The monthly part of the survey is supplemented on a quarterly basis with some quantitative questions, e.g., with respect to firms' capacity utilization. In our analysis we make use of a wide range of explanatory variables that might be relevant to the pricing decision of a firm. Table 1 summarizes these questions.

[2] The IFO-BCS is technically at the product level, so the number of participants does not exactly conform to the number of firms, though we will use that terminology throughout the paper.

Table 1: Questionnaire

Number	Label	Question	Response categories		
Monthly Questions					
Q1	*Production*	Our domestic production activity with respect to product XY have …	increased	roughly stayed the same	decreased
Q2	$E(Production)$	Expectations for the next 3 months: Our domestic production activity with respect to product XY will probably …	increase	remain virtually the same	decrease
Q3	*Price*	Our net domestic sales prices for XY have …	increased	remained about the same	gone down
Q4	$E(Price)$	Expectations for the next 3 months: Our net domestic sales prices for XY will …	increase	remain about the same	decrease
Q5	*Business Situation*	We evaluate our business situation with respect to XY as …	good	satisfactory	unsatisfactory
Q6	*Business Expectations*	Expectations for the next 6 months: Our business situation with respect to XY will in a cyclical view …	improve	remain about the same	develop unfavourably
Q7	*Orders*	Our orders with respect to product XY have …	increased	roughly stayed the same	decreased
Quarterly and Supplementary Questions					
Q8	*Capacity Utilization*	The utilization of our production equipment for producing XY currently amounts to …%.	30% ,40%,…,70%,75%,…,100%, more than 100%		
Q9	*Technical Capacity*	We evaluate our technical production capacity with reference to the backlog of orders on books and to orders expected in the next twelve months as …	more than sufficient	sufficient	less than sufficient
Q10	*Employment Expectations*	Expectations for the next 3 months: Employment related to the production of XY in domestic production unit(s) will probably …	increase	roughly stay the same	decrease

Notes: This table provides the translated questions and response possibilities of the IFO-BCS for manufacturing. For the production questions Q1 and Q2 firms are explicitely asked to ignore differences in the length of months or seasonal fluctuations. For Q8 customary full utilization is defined by 100%.

2.2 Construction of Qualitative Volatilty Measures

The construction of ex-post forecast errors combines past responses of the production expectation question (Q2) with current responses of realized production changes vis-à-vis last month (Q1). We follow Bachmann et al. (2013). To fix ideas, imagine that the production expectation question in the IFO-BCS, Q2, was asked only for the next month instead of the following three months. In this case, when comparing the expectation in month $\tau-1$ with the realization in month τ, nine possibilities arise:[3] the company could have predicted an increase in production and realized one, in which case we would count this as zero forecast error. It could have realized a no change, in which case, we would quantify the expectation error as -1 and, finally, it could have realized a decrease, which counts as -2. Table 2 summarizes the possible expectation errors.

In actuality, the production expectation question in the IFO-BCS is for three months ahead. Suppose that a firm stated in month $\tau-3$ that its production will increase in the next three months. Suppose further that in the next three months one observes the following sequence of outcomes: production increased between $\tau-3$ and $\tau-2$, remained unchanged between $\tau-2$ and $\tau-1$, and production decreased between $\tau-1$ and τ. Due to the qualitative nature of the IFO-BCS we have to make assumptions about the cumulative production change over three months. As a baseline we adopt the following steps. First, we define for each month τ a firm-specific activity variable as the sum of the *Increase* instances minus the

[3] In this section, the time index refers to a month and is denoted by τ.

Table 2: Possible Expectation Errors (One-Month Case)

	Realization in τ		
Expectation in $\tau-1$	*Increase*	*Unchanged*	*Decrease*
Increase	0	-1	-2
Unchanged	+1	0	-1
Decrease	+2	+1	0

Notes: Rows refer to past production change expectations. Columns refer to current production change realizations.

sum of the *Decrease* instances between $\tau-3$ and τ from Q1. Denote this variable by $REALIZ_{i,\tau}$. It can obviously range from $[-3,3]$. The expectation errors are then computed as described in Table 3.

Table 3: Possible Expectation Errors (Three-Month Case)

Expectation in $\tau-3$	$REALIZ_{i,\tau}$	$FE_{i,\tau}^{qual}$
Increase	>0	0
Increase	≤ 0	$(REALIZ_{i,\tau}-1)$
Unchanged	>0	$REALIZ_{i,\tau}$
Unchanged	$=0$	0
Unchanged	<0	$REALIZ_{i,\tau}$
Decrease	<0	0
Decrease	≥ 0	$(REALIZ_{i,\tau}+1)$

Notes: Rows refer to production expectations in the IFO-BCS (Q2) in month $\tau-3$.

Notice that the procedure in Table 3 is analogous to the one month case. Our final expectation error $FE_{i,\tau}^{qual}$ ranges from $[-4,4]$, where for instance -4 indicates a strongly negative forecast error: the company expected production to increase over the next three months, yet every single subsequent month production actually declined. In our study we use the absolute value of $FE_{i,\tau+3}^{qual}$ as a measure of idiosyncratic volatility in period τ of firm i. We denote this variable by $ABSFE_{i,\tau}^{qual}$:

$$ABSFE_{i,\tau}^{qual} = \left| FE_{i,\tau+3}^{qual} \right| . \tag{1}$$

The timing assumption here means that firms realizing large expectation errors in period $\tau+3$ face high uncertainty in period τ, i.e., the timing assumption allows the "wait-and-see" effect of high volatility to shine through.

We also compute a measure of firm-level volatility based on Comin and Mulani (2006) as well as Davis et al. (2006). Using a firm i's expectation errors we can define a symmetric 5-quarter rolling window standard deviation as

$$STDFE_{i,\tau}^{qual} = \frac{1}{5}\sqrt{\sum_k \left(FE_{i,\tau+3+k}^{qual} - \overline{FE}_{i,\tau+3}^{qual} \right)^2}, \tag{2}$$

where $\overline{FE}_{i,\tau+3}^{qual}$ is the average of $FE_{i,\tau+3+k}^{qual}$ for $k=\{-6,-3,0,3,6\}$.

2.3 Construction of Quantitative Volatility Measures

Bachmann and Elstner (2013) argue that the supplementary question about capacity utilization (Q8) allows – under certain assumptions – the construction of quantitative production expectations. To illustrate this we start from the following production relationship of an individual firm i:

$$y_{i,\tau}^{act} = u_{i,\tau} y_{i,\tau}^{pot}, \tag{3}$$

where $y_{i,\tau}^{act}$ denotes the firm's actual output, $y_{i,\tau}^{pot}$ its potential output level, and $u_{i,\tau}$ the level of capacity utilization. Only $u_{i,\tau}$ is directly observable in the IFO-BCS. Taking the natural logarithm and the three-month difference, we get[4]

$$\Delta \log y_{i,\tau}^{act} = \Delta \log u_{i,\tau} + \Delta \log y_{i,\tau}^{pot} \ . \tag{4}$$

Under the assumption that potential output remains constant, i.e., $\Delta \log y_{i,\tau}^{pot} = 0$, percentage changes in actual output can be recovered from percentage changes in capacity utilization. To implement this idea we restrict the analysis to firms for which we can reasonably expect that they did not change their production capacity in the preceding quarter, making use of the questions concerning expected technical production capacity (Q9) and employment expectations (Q10). The existence of non-convex or kinked adjustment costs for capital and labor adjustment as well as time to build (see Davis and Haltiwanger, 1992, as well as Doms and Dunne, 1998) make this a reasonable assumption. To be conservative we require a firm to satisfy both criteria in $\tau - 3$ for us to assume that its production capacity has not changed between $\tau - 3$ and τ. In this case, we use the quarterly percentage change in capacity utilization in τ as a proxy for the quarterly percentage change in production in τ.

If the production capacity can be assumed not to have changed in the preceding quarter, and if, in addition, no change in production was expected three months prior, a change in capacity utilization, $\Delta \log u_{i,\tau}$, is also a production expectation error of firm i in month τ. We thus consider only firms which state in period $\tau - 3$ that their production level (Q2), employment level, and technical production capacity will remain the same in the next three months.[5] We then compute $\Delta \log u_{i,\tau}$ three months later in τ. The resulting measure $\Delta \log u_{i,\tau}$ constitutes our definition of a quantitative production expectation error, which we denote by $FE_{i,\tau}^{quan}$.[6]

[4]Time intervals are again months. For us to construct an expectation error in τ, we need an observation for capacity utilization in τ and $\tau - 3$.

[5]We also clean our sample from firm-quarter observations with extreme capacity utilization statements, i.e., those that exceed 150%, and from firm-quarter observations with "inconsistent" production change statements. To determine the latter we consider the realized production question (Q1) concerning actual production changes in the months τ, $\tau - 1$, $\tau - 2$. We drop all observations as inconsistent in which firms report a strictly positive (negative) change in $\Delta \log u_{i,\tau}$ and no positive (negative) change in Q1 in the last 3 months. For firms that report $\Delta \log u_{i,\tau} = 0$, we proceed as follows: Unless firms in Q1 either answer three times in a row that production did not change, or they have at least one "Increase" *and* one "Decrease" in their three answers, we drop them as inconsistent. In our sample we have $389,546$ firm level observations for $u_{i,\tau}$. The number of outliers is quite small and corresponds to 242 observations. With the remaining observations we are able to compute $349,531$ changes in capacity utilization, $\Delta \log u_{i,\tau}$. For $181,158$ observations we can assume that their $y_{i,\tau}^{pot}$ has not changed during the last three months, due to Q9 and Q10. In the end, we classify $71,437$ observations as "inconsistent" and drop them. Our final sample consists of $109,721$ observations for $\Delta y_{i,\tau}^{act}$.

[6]Firms are asked about their capacity utilization in March, June, September, and December, allowing us to compute quantitative forecast errors between March and June, June and September etc. For the qualitative forecast errors, we could, in principle, compute a three-month-ahead forecast error every month. In the baseline regression analysis, however, we only consider forecast errors based on qualitative production expectations in those same months. As robustness checks, we also run regressions using the (larger) monthly qualitative sample.

We then take the absolute value of $FE^{quan}_{i,\tau+3}$:

$$ABSFE^{quan}_{i,\tau} = \left| FE^{quan}_{i,\tau+3} \right|, \tag{5}$$

where $ABSFE^{quan}_{i,\tau}$ denotes our quantitative idiosyncratic volatility measure of firm i in period τ. Note that we can compute quantitative volatility measures only for firm level observations with constant production expectations as the question concerning production expectations (Q2) is qualitative. The quantitative nature of this measure allows us to give a quantitative interpretation of the relationship between idiosyncratic volatility and the price setting of firms that we can use for our quantitative theory work. We also compute a 5-quarter rolling window standard deviation denoted by $STDFE^{quan}_{i,\tau}$. Note, however, that for $STDFE^{quan}_{i,\tau}$ the number of observations drops by 90% compared to the sample size for $ABSFE^{quan}_{i,\tau}$, because we need to observe a firm's expectation error five times in a row.

2.4 Discussion of Volatility Measures

How do our measures of idiosyncratic volatility/uncertainty relate to each other and to other such measures in the literature, e.g., from Bachmann et al. (2013). The upper panel of Figure 1 plots the cross-sectional mean of $ABSFE^{qual}_{i,\tau}$, i.e., $MEANABSFE^{qual}_{\tau}$, together with the cross-sectional dispersion of expectation errors (see Bachmann et al., 2013) defined as

$$FEDISP^{qual}_{\tau} = \text{std}\left(FE^{qual}_{i,\tau+3} \right). \tag{6}$$

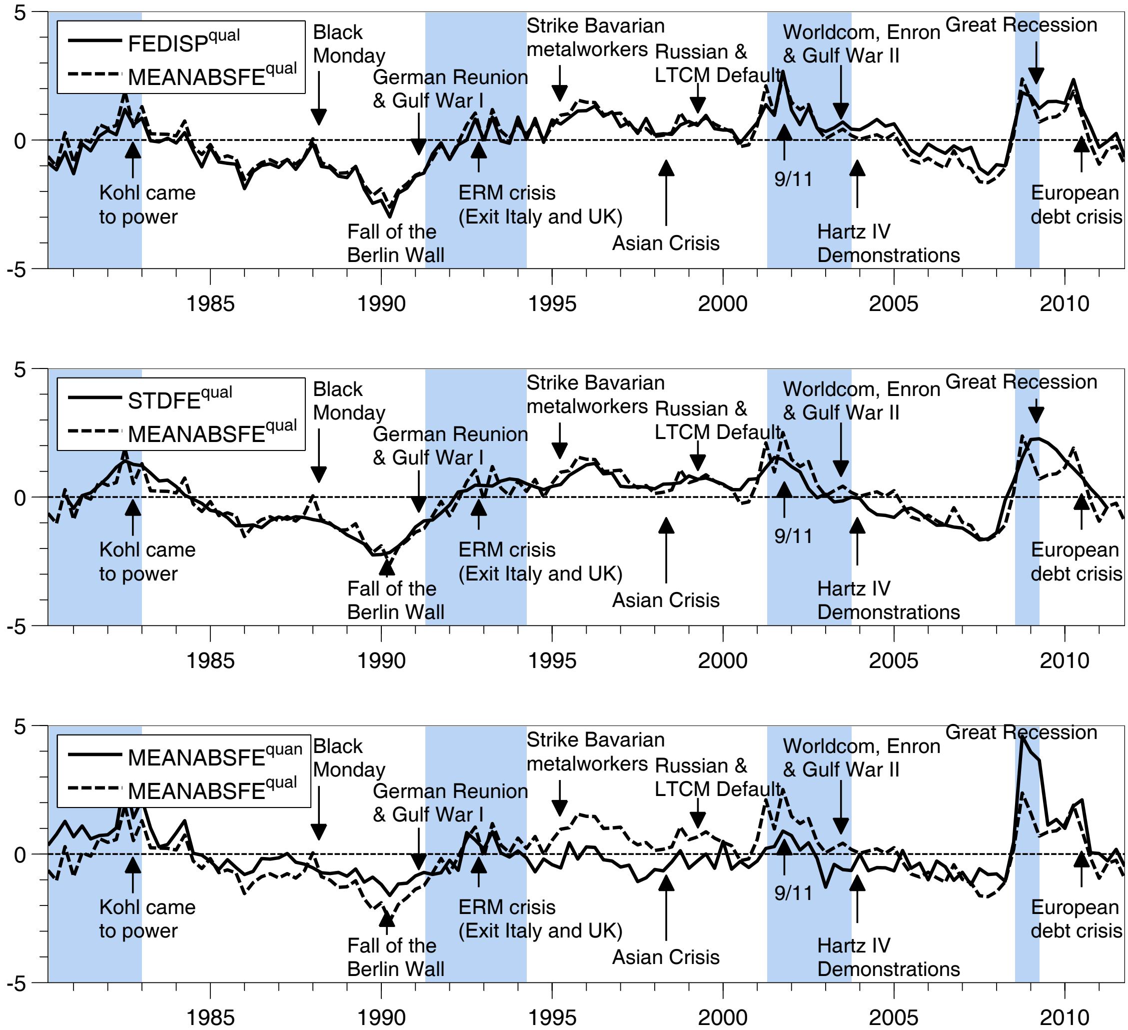
For comparison with the volatility measures based on the *quantitative* forecast errors, we only plot the last month of each quarter for the volatility measures based on the *qualitative* (three-months-ahead) forecast errors, which we have at the monthly frequency. The upper panel of Figure 1 shows that both time series display similar properties - they rise in the wake of the fall of the Berlin Wall, again around 2001, and at the start of the global financial crisis, where they remain elevated with the onset of the European debt crisis. All in all, we see a close link between both idiosyncratic volatility measures. The visual evidence is supported by the high time-series correlation coefficient of 0.94 between $FEDISP^{qual}_{\tau}$ and $MEANABSFE^{qual}_{\tau}$.

The middle panel of Figure 1 shows the cross-sectional mean of $STDFE^{qual}_{i,\tau}$ together with $MEANABSFE^{qual}_{\tau}$. Both time series comove closely with a high positive time-series correlation coefficient of 0.86. This relationship also holds at the firm level: here we find a Spearman correlation coefficient between $ABSFE^{qual}_{i,\tau}$ and $STDFE^{qual}_{i,\tau}$ of 0.47.[7]

The link between the qualitative and the quantitative absolute expectation error is illustrated in the lower panel of Figure 1 where we plot the cross-sectional mean of $ABSFE^{quan}_{i,\tau}$ ($MEANABSFE^{quan}_{\tau}$) together with $MEANABSFE^{qual}_{\tau}$. Both measures of idiosyncratic volatility move reasonably close to each other. The unconditional time-series correlation coefficient between $MEANABSFE^{quan}_{\tau}$ and $MEANABSFE^{qual}_{\tau}$ is 0.62. At the firm level we find a pooled Spearman correlation coefficient between $ABSFE^{qual}_{i,\tau}$ and $ABSFE^{quan}_{i,\tau}$ of 0.65. $MEANABSFE^{qual}_{\tau}$ and $MEANABSFE^{quan}_{\tau}$ are also positively correlated with $FEDISP^{qual}_{\tau}$. Furthermore, all measures are countercyclical: their pairwise time-series

[7] For the quantitative expectation errors we find a Pearson correlation coefficient between $ABSFE^{quan}_{i,\tau}$ and $STDFE^{quan}_{i,\tau}$ of 0.69.

Figure 1: Measures of Idiosyncratic Volatility



Notes: The upper panel shows the quarterly time-series of the average absolute ex-post forecast errors, $MEANABSFE^{qual}$ and of the standard deviation of ex-post forecast errors $FEDISP^{qual}$. The middle panel depicts the quarterly time series of the average absolute ex-post forecast errors, $MEANABSFE^{qual}$ and of the average 5-quarter rolling window standard deviation $STDFE^{qual}$. The lower panel plots the quarterly values of the average absolute ex-post qualitative forecast errors, $MEANABSFE^{qual}$ and the average absolute ex-post quantitative forecast errors, $MEANABSFE^{quan}$. Monthly series are transformed to the quarterly frequency by selecting the last month of each quarter. The sample period is I/1980 - IV/2011. Each series has been demeaned and standardized by its standard deviation. All time series are seasonally adjusted. Shaded regions show recessions as dated by the Economic Cycle Research Institute (ECRI): I/1980 - IV/1982, I/1991 - II/1994, I/2001 - III/2003 and II/2008 - I/2009.

unconditional correlation coefficients with quarter-to-quarter growth rates of production, total hours worked and employment in the West German manufacturing sector are negative (see Table 4).

Table 4: Cross-Correlations

	$FEDISP^{qual}$	$MABSFE^{qual}$	$STDFE^{qual}$	$MABSFE^{quan}$	$STDFE^{quan}$
$\Delta \log Production$	-0.21	-0.26	-0.32	-0.44	-0.19
$\Delta \log Hours$	-0.24	-0.30	-0.34	-0.25	-0.26
$\Delta \log Employment$	-0.41	-0.44	-0.46	-0.26	-0.26
$FEDISP^{qual}$	1.00	0.94	0.86	0.55	0.12
$ABSFE^{qual}$		1.00	0.89	0.62	0.25
$STDFE^{qual}$			1.00	0.68	0.39
$ABSFE^{quan}$				1.00	0.32
$STDFE^{quan}$					1.00

Notes: This table shows the pairwise unconditional time-series correlation coefficients of various activity variables in West German manufacturing together with different measures of idiosyncratic volatility. Volatility measures based on the qualitative forecast errors, which are in principle available at the monthly frequency, are transformed to the quarterly frequency by selecting the last month of each quarter, even for those correlations that only involve qualitative volatility measures. The activity variables are quarter-on-quarter growth of production ($\Delta \log Production$), total hours worked ($\Delta \log Hours$) and employment ($\Delta \log Employment$). The data sources are the Federal Statistical Office and Eurostat. All variables are seasonally adjusted. The sample period is I/1980 - IV/2011.

Further evidence for the appropriateness of our measures comes from disaggregating the time series and analyzing the time-series correlation coefficients for 13 manufacturing industries and 5 firm-size classes separately. The results are summarized in Table 12 in Appendix A. Columns 2 and 3 report correlations for $MEANABSFE_{\tau}^{qual}$ and $FEDISP_{\tau}^{qual}$. All industrial sectors and firm-size classes feature correlation coefficients that are around 0.9 or higher. The last two columns compare $MEANABSFE_{\tau}^{qual}$ and $STDFE_{i,\tau}^{qual}$. Here, the strong relationship decreases somewhat at the disaggregate level, however, most correlations are still in the range of 0.6 and 0.8.

3 Empirical Analysis

In this section we analyze the (conditional) effects of heightened idiosyncratic volatility on the average frequency of price adjustment. We first explain the construction of the other regression inputs and specify the empirical model. We then present the results.

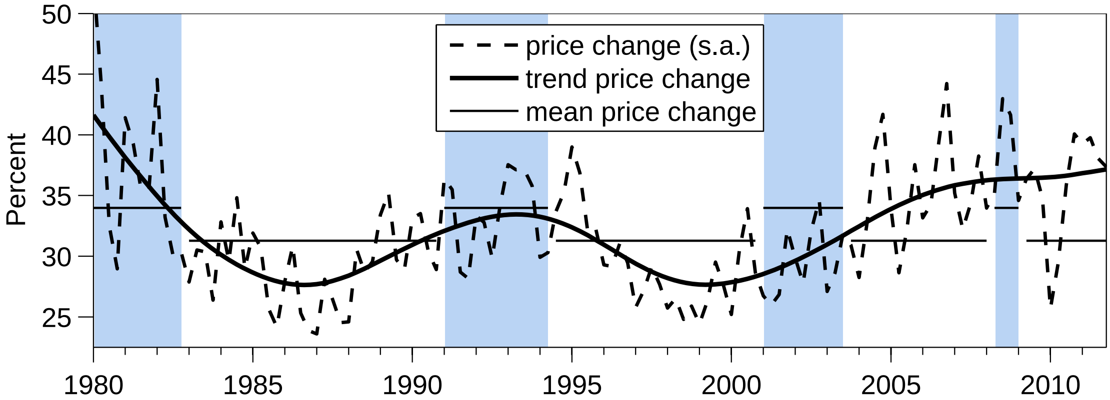
3.1 Construction of Price Variables

Although the IFO-BCS includes price statements at the monthly frequency, other variables used in this approach such as capacity utilization are only available on a quarterly basis. We therefore estimate a quarterly model as the baseline. Thus, we need to transform the monthly price statements to a quarterly frequency. The quarterly price variable is based on question Q3 from Table 1. $Price\ change_{i,t}$ takes the value one if firm i states at date t that it changed its price in at least one of the previous three months, and zero otherwise.[8]

[8]From now on, time is measured in quarters and denoted by t.

Figure 2 provides a graphical illustration of the price frequency variable. The figure plots the seasonally adjusted frequency of price changes (dashed line), i.e., the share of firms that adjusted their price in a given quarter, its HP-filtered trend (thick line), and the recession and non-recession means of the frequency of price changes (thin lines). The frequency of price adjustments moves in a band between 25% and 45% and suggests that on average roughly one third of all firms adjust their prices each quarter at least once. Concerning business cycle properties we find a moderate countercyclicality of the frequency of price changes, on average it is somewhat higher in recessions (33.99%) than in normal times (31.28%).[9] This difference is statistically significant at the 1% level.

Figure 2: Frequency of Price Changes



Notes: The figure shows the seasonally adjusted frequency of quarterly price changes (dashed line), its HP-filtered ($\lambda = 1600$) trend (thick line) and the recession and non-recession means (thin lines). All data is on a quarterly basis. Shaded regions show recessions as dated by the Economic Cycle Research Institute (ECRI): I/1980 - IV/1982, I/1991 - II/1994, I/2001 - III/2003 and II/2008 - I/2009.

3.2 Specification of the Empirical Model

We use a quarterly probit model[10] to estimate the probability of observing a price change, i.e.,

$$P(y_{i,t} = 1\,|\mathbf{x}_{i,t}) = \Phi(\mathbf{x}_{i,t}\mathbf{b}) \ , \tag{7}$$

where $y_{i,t}$ is the dependent variable, the vector $\mathbf{x}_{i,t}$ includes all explanatory variables, $\mathbf{b}$ is the coefficient vector, and Φ is the cumulative distribution function of the standard normal distribution.[11] Robust standard errors are clustered by firm.

Table 5 lists the variables used in the estimation procedure. At the heart of the empirical analysis are the volatility measures described in detail in Section 2. We use two qualitative volatility measures ($ABSFE^{qual}$ and $STDFE^{qual}$) and two quantitative ones ($ABSFE^{quan}$ and $STDFE^{quan}$).[12] Taylor dummies

[9] At the *monthly* frequency, we find for our data that during recessions the frequency of price adjustment is 1.6 percentage points higher. This is in line with the findings of Vavra (2013) who finds that during recessions the frequency of price adjustment is 1.2 percentage points higher for U.S. monthly CPI data. He also reports an average monthly price change frequency of 15.0% which corresponds well to our monthly average of 17.6%.

[10] We also estimated logit and panel-fixed-effects logit models with essentially the same results.

[11] As asymmetries might be important in firms' price setting, we also estimate two specifications which separately model the probability of a price increase and a price decrease. We find that heightened volatility leads to a rise in price dispersion, i.e., it increases both the probability of an increase and that of a decrease. Detailed results are presented in Appendix C.

[12] Recall that for the construction of volatility measures based on quantitative expectation errors we had to restrict our sample

($Taylor1 - Taylor8$) account for the fact that some firms adjust their prices at fixed time intervals. For example, $Taylor2$ takes a value of one if the last time a firm adjusted its price was two quarters ago. We also add time dummies for each quarter (Time-fixed effects) to capture aggregate shocks which influence all firms' prices in the same way, to control for aggregate variables that might influence prices and volatility at the same time, and to account for seasonal patterns in the price-setting behavior of firms.

We also include a number of firm-specific variables. *Capacity Utilization* and *Business Situation* comprise information on the current state of a specific firm. To control for confidence and news aspects (see, e.g., Barsky and Sims, 2012) we include the forward-looking variables *Business Expectation*, *Technical Capacity*, and *Expected Employees*.[13] Changes in input costs are included to capture supply shocks. Lein (2010) emphasizes the important role of intermediate goods costs as a determinant of its price setting. *Orders* are important to account for a possible indirect effect of uncertainty on price setting through demand, insofar this effect is not already captured by the time-fixed effects in the regression, i.e., the possibility that heightened uncertainty may lead to the postponement of projects in other firms, which would decrease the demand for certain goods in the economy.

The qualitative firm-specific variables *Business Situation*, *Business Expectations*, *Orders*, *Technical Capacity*, and *Expected Employees* have three possible response categories (see Table 1), e.g., firms can appraise their current state of business as good, satisfactory, or unsatisfactory. To account for possible asymmetric effects we include these variables with both positive and negative values separately. For example, the variable *Business Situation* is divided into two sub-variables. If firm i at time t reports its state as good, the variable $Statebus^{+}_{i,t}$ is equal to one, and the variable $Statebus^{-}_{i,t}$ is equal to zero. If the firm answers that its state is unsatisfactory, $Statebus^{+}_{i,t}$ is equal to zero, and $Statebus^{-}_{i,t}$ is equal to one. If the firm believes that its state is satisfactory, both $Statebus^{+}_{i,t}$ and $Statebus^{-}_{i,t}$ are equal to zero, which is the baseline. We proceed analogously with *Business Expectations*, *Orders*, *Technical Capacity*, and *Expected Employees*.

The IFO-BCS contains no direct information about input costs, which is why we construct a variable that proxies the change in the cost of input goods for each sector k for each time period ($\Delta Costs_{k,t}$) following Schenkelberg (forthcoming). $\Delta Costs_{k,t}$ for each sector is calculated as the weighted average of net price changes of (input) goods from all sectors. The weights are derived from the relative importance of the sectors in the production of goods in sector k.[14]

Before the first price change of an individual firm we do not know how much time elapsed since the last price change. This poses a problem if time-dependent pricing is important for price setting. We, therefore, drop all observations of a firm prior to the first price change. In addition, whenever an observation in the price change variable is missing in the period between two price changes, the whole period is discarded from the sample as we do not know whether the missing observation is associated with a price change (see, e.g., Loupias and Sevestre, 2013).

to firms with constant production expectations. Figure 4 in the appendix shows that the correlation of the frequency of price changes between the entire sample and the one based on qualitative expectation errors ($\rho = 0.92$), the entire and the quantitative ($\rho = 0.80$), and the qualitative and the quantitative samples ($\rho = 0.91$) is very high. We also ran the estimation using $ABSFE^{qual}$ on the restricted sample that we use in the regressions with $ABSFE^{quan}$, and the results are robust.

[13] Note that in the construction of the volatility measures based on quantitative forecast errors, we have to restrict our sample to firms that report no change in *Technical Capacity* and *Expected Employees*. Therefore these variables are not included in the regressions when we use the quantitative volatility measures.

[14] See Appendix B for a detailed description.

Table 5: Description of Variables

Label	Variable	Response	Scale
Taylor dummies	$Taylor1 - Taylor8$		Binary
Sector dummies	$Sector1 - Sector14$		Binary
Capacity Utilization	$Capacity\ utiliz.$	30%, 40%...70%, 75%, 80%...100%...	Interval
Cost of Input Goods	$\Delta Costs$	$-0.42 \ldots 0.87$	Interval
Business Situation	$Statebus^{+}$	good	Binary
	$Statebus^{-}$	unsatisfactory	Binary
Business Expectation	$Expbus^{+}$	increase	Binary
	$Expbus^{-}$	decrease	Binary
Orders	$Order^{+}$	increase	Binary
	$Order^{-}$	decrease	Binary
Technical Capacity	$Tech.capacity^{+}$	more than sufficient	Binary
	$Tech.capacity^{-}$	less than sufficient	Binary
Expected Employees	$Expempl^{+}$	increase	Binary
	$Expempl^{-}$	decrease	Binary
Time-fixed effects	$Time1 \ldots$		Binary
Qualitative idiosyncratic volatility	$ABSFE^{qual}$		Ordinal
Quantitative idiosyncratic volatility	$ABSFE^{quan}$		Interval
Qualitative idiosyncratic volatility	$STDFE^{qual}$		Interval
Quantitative idiosyncratic volatility	$STDFE^{quan}$		Interval
Price change in last 3 months	$Price\ change$	change	Binary

3.3 Baseline Results

The estimation results of the pooled probit benchmark models with *Price change* as the dependent variable are presented in Table 6. The first four models – Columns (1) to (4) – include a set of sector, Taylor and time-fixed effects dummies and a constant. The other four models – Columns (5) to (8) – contain, in addition, the set of firm-specific variables described in Table 5. Each of the eight models includes one volatility measure. Models (1) and (5) use the absolute qualitative forecast error, $ABSFE^{qual}$, (2) and (6) the absolute quantitative forecast error, $ABSFE^{quan}$, (3) and (7) the 5-quarter rolling window standard deviation of firms' qualitative expectation errors, $STDFE^{qual}$, and (4) and (8) the 5-quarter rolling window standard deviation of firms' quantitative expectation errors, $STDFE^{quan}$.

The table reports marginal effects. Quantitative variables ($Capacity\ utiliz.$, $\Delta Costs$, $ABSFE^{qual}$, $ABSFE^{quan}$, $STDFE^{qual}$, and $STDFE^{quan}$) are evaluated at their respective sample averages. Qualitative variables are evaluated at zero, i.e., "satisfactory" ($Statebus^{+}$, $Statebus^{-}$), "remain about the same" ($Expbus^{+}$, $Expbus^{-}$, $Expempl^{+}$, $Expempl^{-}$), "roughly stayed the same" ($Orders^{+}$, $Orders^{-}$), or "sufficient" ($Tech.\ capacity^{+}$, $Tech.\ capacity^{-}$). Marginal effects for the dummy variables are calculated as the difference in the probability of a price change as the dummy switches from 0 to 1.

Table 6: Benchmark Results (Pooled Probit Model) for Price Change

Dependent variable: Price change								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$ABSFE^{qual}$	0.012***				0.008***			
	(0.001)				(0.002)			
$ABSFE^{quan}$		0.097***				0.092***		
		(0.020)				(0.024)		
$STDFE^{qual}$			0.035***				0.016***	
			(0.003)				(0.002)	
$STDFE^{quan}$				0.191				0.032
				(0.132)				(0.132)
Capacity utiliz.					0.001***	0.001***	0.000***	0.001
					(0.000)	(0.000)	(0.000)	(0.001)
Δ Costs					0.224***	0.313***	0.056***	0.032
					(0.021)	(0.037)	(0.016)	(0.100)
$Statebus^{+}$					0.034***	0.039***	0.022***	0.065***
					(0.004)	(0.006)	(0.003)	(0.020)
$Statebus^{-}$					0.047***	0.064***	0.029***	0.060*
					(0.004)	(0.009)	(0.003)	(0.035)
$Expbus^{+}$					0.018***	0.019**	0.008***	0.011
					(0.004)	(0.008)	(0.003)	(0.027)
$Expbus^{-}$					0.057***	0.040***	0.039***	0.014
					(0.004)	(0.008)	(0.004)	(0.024)
$Orders^{+}$					0.076***	0.064***	0.048***	0.069***
					(0.004)	(0.006)	(0.004)	(0.023)
$Orders^{-}$					0.060***	0.048***	0.035***	0.078***
					(0.004)	(0.006)	(0.003)	(0.024)
Tech. $capacity^{+}$					0.013***		0.007***	
					(0.004)		(0.003)	
Tech. $capacity^{-}$					0.050***		0.028***	
					(0.006)		(0.005)	
$Expempl^{+}$					0.029***		0.015***	
					(0.006)		(0.004)	
$Expempl^{-}$					0.030***		0.018***	
					(0.004)		(0.003)	
Observations	249,363	62,982	210,864	6,960	198,297	55,370	169,148	6,239
Pseudo R-squared	0.121	0.131	0.135	0.197	0.133	0.137	0.145	0.206

*** p<0.01, ** p<0.05, * p<0.1

Notes: The table reports marginal effects. Robust and clustered (by firm) standard errors are in parentheses. Included in the pooled probit model but not shown in the table are time-fixed effects for each quarter, sector-specific dummies, and Taylor dummies. Monthly series are transformed to the quarterly frequency by selecting the last month of each quarter. $ABSFE^{qual}$: qualitative idiosyncratic volatility; $ABSFE^{quan}$: quantitative idiosyncratic volatility; $STDFE^{qual}$: 5-quarter rolling window standard deviation of a firm's qualitative expectation errors; $STDFE^{quan}$: 5-quarter rolling window standard deviation of a firm's quantitative expectation errors.

Perhaps unsurprisingly, costs of intermediate goods are the most important determinant of firms' pricing decisions. Both good and unsatisfactory current business situations, increasing and decreasing business expectations and order levels as well as a higher capacity utilization lead to a higher probability of price change.

The takeaway from Table 6 for our research question is the following: regardless of the way volatility is measured and regardless of whether firm-specific variables are included, higher volatility increases the probability of a price change. The signs of the marginal effects of $ABSFE^{qual}$ show that higher volatility increases the probability of a price change in both specifications (see Columns (1) and (5)). However, the size of the marginal effects of $ABSFE^{qual}$ is difficult to interpret. In contrast, the marginal effects for $ABSFE^{quan}$ imply that prices are about 0.1 percentage points more likely to change when the corresponding measure of volatility changes by one percentage point. To put this into perspective, in the recent financial crisis we observed that business volatility increased by 7.6 percentage points.

Turning to the rolling window proxies, we find that the marginal effects for $STDFE^{qual}$ are also positive. The marginal effects of $STDFE^{quan}$ are positive but statistically insignificant. This is likely due to the fact that the number of observations is much smaller compared to all other regressions.

To sum up, we find that idiosyncratic volatility is a statistically significant determinant of the price setting behavior of firms. Economically, however, the effects are small.

4 Model Evidence

4.1 New Keynesian DSGE model

Our empirical results show that an increase in firm-specific volatility leads to an increase in the probability of a price change. To assess the quantitative consequences of this finding for the effectiveness of monetary policy, we use a standard New Keynesian DSGE model (see, e.g., Galí, 2008) where price setting is constrained à la Calvo (1983). The induced price rigidities are the only source of monetary non-neutrality and are captured by the Calvo parameter which fixes the probability of a price change for a given firm. Due to the absence of selection effects (see, e.g., Golosov and Lucas, 2007), the Calvo model generates a larger degree of monetary non-neutrality compared to a menu cost model, making it a natural, conservative choice for our exercise, i.e., giving the volatility effect on monetary policy through endogenous movements of price rigidity the best possible chance to shine through. Given the uncovered empirical relationship between an increase in firm-specific volatility and the probability of a price change, we model a change in firm-specific volatility through a change in the Calvo parameter. Given that the model is standard, our exposition is kept short.

4.1.1 Households

We assume that a representative household chooses a composite consumption good, C_t, and supplies labor, L_t, in order to maximize

$$U = E_0 \sum_{t=0}^{\infty} \beta^t \left[\frac{C_t^{1-\sigma}}{1-\sigma} - \psi \frac{L_t^{1+\phi}}{1+\phi} \right] , \tag{8}$$

where $\psi \geq 0$ scales the disutility of labor, σ defines the constant relative risk aversion parameter and ϕ is the inverse of the Frisch elasticity of labor supply. Given the aggregate price index P_t, the household faces the following budget constraint

$$C_t + \frac{B_t}{P_t} = \frac{W_t}{P_t} L_t + \frac{B_{t-1}}{P_{t-1}} \frac{R_{t-1}}{\pi_t} + \Xi_t \ , \tag{9}$$

where income from supplying labor, L_t, at wage W_t, from investment in the nominal bond, B_{t-1}, at the risk free rate R_{t-1}, and from the profits of the intermediate goods firms, Ξ_t, is spent on consumption, C_t, and purchases of new bonds, B_t. All variables are deflated by the consumer price; the overall inflation rate is defined as $\pi_t = P_t / P_{t-1}$.

4.1.2 Final Good Firms

Competitive final good firms bundle intermediate goods into a final good, Y_t. Using $i \in [0,1]$ to index intermediate goods, the CES aggregation technology of final good firms is given by

$$Y_t = \left[\int_0^1 Y_{it}^{\frac{\varepsilon-1}{\varepsilon}} di \right]^{\frac{\varepsilon}{\varepsilon-1}} \ , \tag{10}$$

where ε measures the substitution elasticity between intermediate goods and, in equilibrium, $C_t = Y_t$. Expenditure minimization implies the aggregate price index

$$P_t = \left(\int_0^1 P_{it}^{1-\varepsilon} di \right)^{\frac{1}{1-\varepsilon}} \ . \tag{11}$$

4.1.3 Intermediate Good Firms

Intermediate goods are produced under imperfect competition according to the production technology

$$Y_{it} = A_t L_{it}^{1-\alpha} \ , \tag{12}$$

where L_{it} measures the amount of labor employed by firm i and A_t denotes aggregate productivity.

Price setting is constrained à la Calvo (1983), i.e., each period, an intermediate firm is able to re-optimize its price with probability $1-\theta$, $0 < \theta < 1$. Given this possibility, a generic firm i sets P_{it} in order to maximize its discounted stream of future profits

$$\max \ E_t \sum_{k=0}^{\infty} \theta^k \Lambda_{t,t+k} \left[\frac{P_{it}}{P_{t+k}} - MC_{i,t+k}^r \right] Y_{i,t+k} \tag{13}$$

subject to the demand for its variety $Y_{i,t+k} = \left(\frac{P_{it}}{P_{t+k}} \right)^{-\varepsilon} Y_{t+k}$. Here, $\Lambda_{t,t+k}$ denotes the stochastic discount factor and $MC_{i,t+k}^r$ are the firm's real marginal costs.

4.1.4 Monetary Policy

Monetary policy is conducted according to a Taylor rule that responds to inflation

$$\frac{R_t}{\overline{R}} = \left(\frac{\pi_t}{\overline{\pi}} \right)^{\gamma} v_t \ , \tag{14}$$

where $\overline{R}$ and $\overline{\pi}$ are the steady state real interest rate and inflation rate, respectively. The innovation to monetary policy follows an AR(1)-process $\log v_t = \rho_v \log v_{t-1} + \varepsilon_t^m$ where ε_t^m is a zero mean white noise process.

4.1.5 Calibration

We calibrate the log-linearized model using standard values from Galí (2008). Table 7 presents the calibrated parameter values. The model period is one quarter. The parameter ψ is chosen such that the representative household devotes one third of her time to work. For the experiments following in the next subsection, we use the period prior to the Great Recession, i.e., from 1980Q1 to 2008Q1, to calibrate the steady-state price frequency of the model. In this time span, on average 31.56% of firms adjust their price in a given quarter, corresponding to a Calvo parameter, θ, of 0.6844.

Table 7: Parameter Values

Parameter		Value
Steady state inflation rate	$\overline{\pi}$	1
Discount Factor	β	0.99
Constant relative risk aversion	σ	1
Inverse elasticity of labor supply	ϕ	1
Labor disutility	ψ	5
Elasticity of substitution	ε	6
Calvo parameter (baseline)	θ	0.684
Returns to scale	$1-\alpha$	0.67
Taylor rule coefficient of inflation	γ	1.5
AR(1)-coefficient of monetary shock	ρ_v	0.5

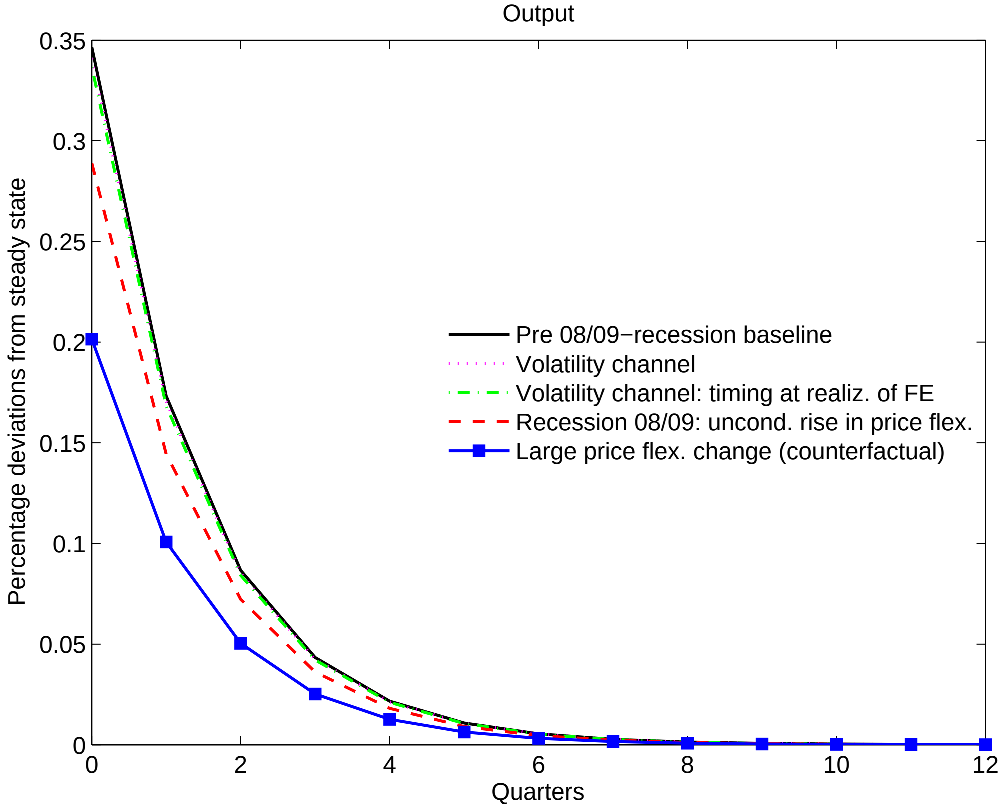
4.2 Volatility, Price Setting, and the Effectiveness of Monetary Policy

Using this New Keynesian business cycle model, we are now able to conduct a number of experiments to flesh out the connection between firm-level volatility, price flexibility, and the effectiveness of monetary policy. In our baseline economy, a 25 basis point monetary policy shock leads, on impact, to a 0.3465 percent deviation of output from its steady state (solid black line in Figure 3), which is in line with the findings of, e.g., Christiano, Eichenbaum, and Evans (2005) and Smets and Wouters (2007). During the 08/09-recession, the average share of firms adjusting their price in a given quarter increased by 7.04 percentage points to 38.6%,[15] translating to a θ of 0.614. In this environment, a 25 basis point monetary policy shock has an impact multiplier of 0.289, i.e., monetary policy loses almost 17% of its effect on output compared to the pre-08/09-recession baseline scenario (dashed red line in Figure 3). In other words, had the increase in observed price flexibility been entirely due to increased business volatility, time-varying volatility would indeed be a quantitatively important determinant of the effectiveness of monetary policy.

Our microeconometric analysis enables us to quantify how much of this loss in effectiveness is directly attributable to an increase in firm-level volatility. Our quantitative volatility measure, $ABSFE^{quan}$, has a

[15] We arrive at this number, which we highlight in the introduction, by fitting a regression of the seasonally adjusted frequency of price changes on a constant and an 08/09-recession dummy.

Figure 3: Impulse Responses to 25 Basis Point Monetary Policy Shock



Notes: Solid black line: baseline price flexibility ($\theta = 0.684$); dotted magenta line: increased price flexibility attributed to increase in volatility in 08/09 recession ($\theta = 0.677$); dash-dotted green line: increased price flexibility attributed to increase in volatility in 08/09 recession (estimate with timing at realization of forecast error) ($\theta = 0.672$); dashed red line: increased price flexibility in 08/09 recession ($\theta = 0.614$); solid blue line with squares: large price flexibility change counterfactual where price flexibility increases by 18 percentage points ($\theta = 0.502$). The horizontal axis indicates quarters; the vertical axis measures percentage deviations from steady state.

pre-recession sample (1980Q1-2008Q1) mean of 4.7. In the third quarter of 2008, right at the height of the financial crisis, our measure reaches its sample maximum of 12.3, an increase of 7.6 percentage points.[16] We can use our empirical model to compute the change in the probability of a price-adjustment due to this increase in business volatility and translate it into an unforeseen, permanent, and once-and-for-all reduction in the model's Calvo parameter of 0.007.[17] The dotted magenta line in Figure 3 shows the response of output in this high-volatility environment to a 25 basis point monetary policy shock. The response is essentially indistinguishable from the response of the baseline model. The impact multiplier is now 0.3409, only 1.6% lower than in the baseline environment. We conclude that it does not appear to be the volatility channel that is at the heart of the increase in price flexibility and the subsequent loss in effectiveness of monetary policy during the 08/09-recession.

[16]These numbers explain why we speak of a tripling of volatility in the abstract and the introduction.

[17]Specifically, we first re-estimate the empirical baseline model on the 1980Q1-2008Q1 sample. We then compute the marginal effects of volatility at the non-recession mean of 4.7 and the 08/09-recession peak of 12.3, thus taking nonlinearities into account. The difference in marginal effects then directly translates into the change of the Calvo parameter. To get an upper bound of the volatility effect, we use the point estimates of the empirical model without firm-specific effects (Column 2 in Table 6) for the experiments as they are slightly larger than those with the firm-specific effects included.

In the next section, we will conduct a number of robustness checks. We find the largest marginal effect for $ABSFE^{quan}$ for the specification where we change the timing structure such that the realized expectation error is contemporaneous with the pricing decision. This specification maximizes the impact of the volatility effect relative to the "wait-and-see" effect and thus it is no surprise to see this increase in the marginal effects. Repeating the above experiment on the basis of this estimate yields an implied reduction of the Calvo parameter of 0.012. The dash-dotted green line in Figure 3 shows the model response for this case. The impact multiplier declines to 0.337, which is 2.9% lower than in the baseline case. This decline still accounts for only one sixth of the unconditional price effect (the 17% loss mentioned above).

We also compute a (counterfactual) scenario where we take the difference between a time of very low price flexibility (1998Q3) and a time when firms were changing prices much more rapidly (2008Q3) and feed this 18 percentage-point change in the Calvo parameter into the model. We use this number to get a rough estimate of the maximum change in monetary non-neutrality over our sample. The resulting impulse response function of output to a 25 basis point monetary policy shock for this case is shown in Figure 3 (solid blue line with squares). The impact deviation of output from its steady state is now only 0.2015, almost 42% lower than in our baseline calibration. This number is close to the 55%-loss in the effectiveness of monetary policy that Vavra (2013) finds between times of high and low volatility.

5 Robustness Checks

The results of the econometric baseline model show that the probability of price adjustment increases by 0.092 percentage points when business volatility rises by one percentage point as measured by the absolute expectation errors (see the sixth column in the upper panel of Table 8). We now conduct a battery of robustness checks for the empirical exercise.

The first robustness check (Table 8, middle panel) concerns the timing of the firm-specific volatility measures, especially for $ABSFE^{qual}$ and $ABSFE^{quan}$. The idea behind our baseline timing assumption is that a realized expectation error in quarter $t+1$ indicates that a firm was uncertain at the time of expectation formation t. In this robustness check, we change the timing structure such that the realized expectation error is contemporaneous with the pricing decision. This timing assumption is likely to make the volatility effect stronger and indeed for $ABSFE^{qual}$ and $ABSFE^{quan}$ we find marginal effects that are twice as large as those of the baseline model.

The second robustness check (Table 8, lower panel) deals with the possibility that some price changes today were already planned in the past. Today's prices may not, therefore, react to current events. Some firms have long-term contracts with their buyers (see, for instance, Stahl, 2010); these contracts might fix prices for some time or change them each period in pre-defined steps. Firms may, therefore, rely on some form of pricing plan. As a robustness check, we drop all observations where price changes were putatively set in the past. These price changes are identified with the help of Q4 – the survey question relating to price expectations for the next 3 months (see Table 1).[18] Thus, in this exercise, we focus on price changes that are unexpected and see whether they react to idiosyncratic volatility. With a value of 0.068, the marginal effect of $ABSFE^{quan}$ is somewhat smaller than that in the baseline model.

We also check whether our estimated coefficients differ between recession and non-recession times. This is not the case as Table 9 shows.

[18] To be concrete, we only include price changes where firms stated a quarter before that they do not expect a price change.

For the construction of the quantitative volatility measures, we imposed a number of restrictions on our sample. First, we only looked at firms that had constant production expectations in order to capture production expectation errors. Since our baseline results show that the volatility effect dominates empirically, we also check whether we get the same results if we focus on production changes as opposed to production expectation errors. Table 10 (upper panel) says yes. If, in addition, we relax the assumption of constant potential output, i.e., we now simply base our volatility measures on utilization changes, the results are still robust (see Table 10, middle panel). Finally, we do a similar exercise for the volatility measures based on qualitative production expectation errors (see Table 10, lower panel). To be specific, we use $REALIZ_{i,t}$ instead of $FE_{i,t}^{qual}$ in the definition of ABS (see Equation 5). Our results remain essentially unchanged.

One might be concerned that measurement error contaminates our production forecast error measures. To deal with this problem, we use the so-called control function approach (see Rivers and Vuong, 1988; Wooldridge, 2002; Imbens and Wooldridge, 2007), a two-stage instrumental variable procedure that can also be applied to nonlinear models. In the first stage we regress each forecast error type on the level of capacity utilization, the change of input costs, two dummies for the business situation, two dummies for the change of orders (see Table 5),[19] plus Taylor and sector dummies, and time-fixed effects. Since firms by definition do not react to measurement error, the idea behind this first stage is to extract that component of the measured forecast error to which firms react with observable actions and thus the true forecast error. In the second stage we estimate our baseline probit model which includes our volatility measures on the right hand side (plus Taylor and sector dummies and time-fixed effects), and the residual from the first stage regression as an additional control variable. Including the residual from the first stage directly controls for any potential endogeneity in our volatility measures. The results are essentially unchanged. Also, the second-stage coefficient of the first-stage residual is statistically not distinguishable from zero, which means that endogeneity issues do not appear to be problem.

In the next exercise we shorten the rolling window from 5 to 3 quarters to increase the number of observations in the construction of the $STDFE$ measures. In particular, the findings for $STDFE^{quan}$ are affected by this issue: the number of observations increases for $STDFE^{quan}$ from 6,239 to 14,458 for the model specification including all firm-specific variables. The estimation results are shown in Table 11. Perhaps unsurprisingly, the coefficient on $STDFE^{quan}$ is now statistically significant. The point estimate for the elasticity is more than twice as high as the elasticity for $ABSFE^{quan}$, which, however, is largely explained by the lower standard deviation of $STDFE^{quan}$. In terms of the change in the Calvo parameter, we find effects of a similar magnitude as for $ABSFE^{quan}$.

The final two robustness checks only concern the qualitative measures of volatility, $ABSFE^{qual}$ and $STDFE^{qual}$. Unlike for the volatility measures based on quantitative expectation errors, there is nothing that prevents us from computing these volatility measures at a monthly frequency. Hence, we redo our baseline estimations also for the monthly frequency with basically unchanged results (see Panel (c) of Table 11).[20]

In the last exercise, we construct a binary firm-level volatility measure that just takes the value one at time t if there is a realized expectation error in $t+1$. Again, our results remain the same (see Panel (d) of Table 11).

[19] Of course, these regressors are excluded in the second stage.

[20] Of course, we exclude the quarterly variables *Capacity Utilization*, *Technical Capacity*, and *Expected Employees*.

Table 8: Robustness I

Dependent variable: Price change								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Baseline results (pooled probit model)				
$\text{ABSFE}^{\text{qual}}$	0.012***				0.008***			
	(0.001)				(0.002)			
$\text{ABSFE}^{\text{quan}}$		0.097***				0.092***		
		(0.020)				(0.024)		
$\text{STDFE}^{\text{qual}}$			0.035***				0.016***	
			(0.003)				(0.002)	
$\text{STDFE}^{\text{quan}}$				0.191				0.032
				(0.132)				(0.132)
				Volatility proxy at time of realization (pooled probit model)				
$\text{ABSFE}^{\text{qual}}$	0.022***				0.008***			
	(0.001)				(0.001)			
$\text{ABSFE}^{\text{quan}}$		0.187***				0.111***		
		(0.021)				(0.020)		
$\text{STDFE}^{\text{qual}}$			0.025***				0.009***	
			(0.002)				(0.002)	
$\text{STDFE}^{\text{quan}}$				0.014				-0.095
				(0.073)				(0.086)
				Unexpected price changes (pooled probit model)				
$\text{ABSFE}^{\text{qual}}$	0.008***				0.005***			
	(0.001)				(0.001)			
$\text{ABSFE}^{\text{quan}}$		0.083***				0.068***		
		(0.015)				(0.016)		
$\text{STDFE}^{\text{qual}}$			0.027***				0.020***	
			(0.003)				(0.003)	
$\text{STDFE}^{\text{quan}}$				0.127				0.015
				(0.137)				(0.173)

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Notes: The table presents marginal effects. Robust and clustered (by firm) standard errors are in parentheses. First panel: baseline results; second panel: alternative timing where realized expectation error is contemporaneous with the pricing decision; third panel: we only consider price changes that are putatively unexpected. Included in all models but not shown in the table are time-fixed effects for each quarter, sector-specific dummies, and Taylor dummies. Models (5) and (7) include, in addition, all firm-specific variables described in Table 5. Model (6) and (8) include the same firm-specific variables except *Technical Capacity* and *Expected Employees*. $ABSFE^{qual}$: qualitative idiosyncratic volatility; $ABSFE^{quan}$: quantitative idiosyncratic volatility; $STDFE^{qual}$: 5-quarter rolling window standard deviation of a firm's qualitative expectation errors; $STDFE^{quan}$: 5-quarter rolling window standard deviation of a firm's quantitative expectation errors.

Table 9: Robustness Checks II: Sample-split into non-recession and recession samples

Dependent variable: Price change								
	Non-recession				Recession			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
$ABSFE^{qual}$	0.009***		0.004***		0.010***		0.005**	
	(0.001)		(0.001)		(0.002)		(0.003)	
$ABSFE^{quan}$		0.063***		0.047***		0.078**		0.064
		(0.015)		(0.014)		(0.032)		(0.041)
$STDFE^{qual}$	0.032***		0.014***		0.034***		0.015***	
	(0.003)		(0.003)		(0.004)		(0.003)	
$STDFE^{quan}$		0.200		0.041		0.062		-0.023
		(0.153)		(0.147)		(0.134)		(0.118)

*** p<0.01, ** p<0.05, * p<0.1

Notes: The table reports marginal effects. Robust and clustered (by firm) standard errors are in parentheses. Included in the pooled probit model but not shown in the table are time-fixed effects for each quarter, sector-specific dummies, and Taylor dummies. Models (3)-(4) include, in addition, firm-specific variables; $ABSFE^{qual}$: qualitative idiosyncratic volatility; $ABSFE^{quan}$: quantitative idiosyncratic volatility; $STDFE^{qual}$: 5-quarter rolling window standard deviation of a firm's qualitative expectation errors; $STDFE^{quan}$: 5-quarter rolling window standard deviation of a firm's quantitative expectation errors.

Table 10: Robustness Checks III

Dependent variable: Price change				
	(1)	(2)	(3)	(4)
	Volatility based on production changes			
ABS^{quan}	0.100***		0.095***	
	(0.017)		(0.021)	
STD^{quan}		0.145**		0.082
		(0.068)		(0.061)
	Volatility based on capacity utilization changes			
ABS^{quan}	0.120***		0.101***	
	(0.010)		(0.012)	
STD^{quan}		0.183***		0.127***
		(0.019)		(0.020)
	Qualitative production change			
ABS^{qual}	0.028***		0.016***	
	(0.001)		(0.002)	
STD^{qual}		0.038***		0.015***
		(0.003)		(0.002)

*** p<0.01, ** p<0.05, * p<0.1

Notes: The table presents marginal effects. All estimations are based on the pooled probit model. First panel: volatility measure based on production changes as opposed to production expectation errors; second panel: volatility measure based on capacity utilization changes; third panel: qualitative production realization as volatility measure (i.e., $REALIZ_{i,t}$ replaces $FE^{qual}_{i,t}$ in Equation 5). Robust and clustered (by firm) standard errors are in parentheses. Included in all models but not shown in the table are time-fixed effects for each quarter, sector-specific dummies, and Taylor dummies. Models (3) and (4) include, in addition, all firm-specific variables described in Table 5, except *Technical Capacity* and *Expected Employees* in the specification of the first panel.

Table 11: Robustness Checks IV

Dependent variable: Price change				
	(1)	(2)	(3)	(4)
	(a) Control function approach			
$\text{ABSFE}^{\text{qual}}$	0.012***		–	
	(0.002)			
$\text{ABSFE}^{\text{quan}}$		0.099***		–
		(0.024)		
	(b) 3-quarter rolling window standard deviation			
$\text{STDFE}^{\text{qual}}$	0.040***		0.019***	
	(0.003)		(0.003)	
$\text{STDFE}^{\text{quan}}$		0.235***		0.182**
		(0.076)		(0.077)
	(c) Monthly model			
$\text{ABSFE}^{\text{qual}}$	0.004***		0.002**	
	(0.001)		(0.001)	
$\text{STDFE}^{\text{qual}}$		0.011***		0.005***
		(0.001)		(0.001)
	(d) Volatility measure as dummy variable			
$\text{ABSFE}^{\text{qual}}$	0.017***		0.010***	
	(0.002)		(0.003)	

*** p<0.01, ** p<0.05, * p<0.1

Notes: The table presents marginal effects. All estimations are based on the pooled probit model. First panel: control function approach where the second stage includes time-fixed effects, sector dummies, Taylor dummies, and the residual of the first stage; second panel: 3-quarter rolling window instead of the baseline 5-quarter one; third panel: volatility measure computed from monthly three-month-ahead qualitative production forecast errors; fourth panel: binary volatility measure that takes the value one at time t if there is a realized expectation error in $t+1$. Robust and clustered (by firm) standard errors are in parentheses. Included in the pooled probit model but not shown in the table are time-fixed effects, sector-specific dummies, and Taylor dummies. Models (3) and (4) include, in addition, all firm-specific variables described in Table 5 except *Capacity Utilization*, *Technical Capacity* and *Expected Employees* for the monthly model which are all at a quarterly frequency and except *Technical Capacity* and *Expected Employees* for the quantitative models. Taylor dummies in the monthly model are defined with respect to the last *month* in which a firm resets its price, e.g., *Taylor*2 takes a value of one if the last time a firm adjusted its price was two months ago. As in the quarterly specifications, we include two years worth of Taylor dummies.

6 Conclusion

The contribution of this paper is threefold. Using micro data from West German manufacturing firms provided by the IFO-BCS, we construct measures of firm-level volatility, which, in addition, are also meant to capture firm-level uncertainty. Specifically, we compute firm-specific expectation errors and use their absolute values and rolling-window standard deviations as measures of idiosyncratic business volatility. Second, we find that the frequency of price adjustment increases in idiosyncratic volatility. Third, the total quantitative impact of firm-level volatility on the frequency of price adjustment of firms is small. Monetary policy therefore does not lose much of its effectiveness in the stabilization of real output in times that are characterized *only* by high idiosyncratic volatility.

This last point is particulary important for economic decision makers. Recent evidence points to volatility/uncertainty playing a role in the decision-making process of central bankers (e.g., Jovanovic and Zimmermann, 2010; Bekaert, Hoerova, and Lo Duca, 2010; Kohlhas, 2011). Our analysis, however, shows that the role of heightened volatility (and of uncertainty) might be of minor concern for the conduct of traditional monetary policy. Of course, our analysis is mute on issues like the interaction of volatility/uncertainty with financial frictions, a channel a growing recent literature has emphasized, and which might become more important as monetary policy is viewed as increasingly responsible for ensuring financial stability. More generally, it seems important to understand why price rigidities seem to change so significantly over the business cycle and which consequences for monetary policy these fluctuations in the extensive margin of price setting might have.

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A Link between $FEDISP$ and $MEANABSFE$

Table 12: Time Series Correlation Coefficients between $FEDISP_t$ and $MEANABSFE_{i,t}$

Group of Firms	Correlation between $MEANABSFE_{i,t}^{qual}$ and $FEDISP_t^{qual}$ raw data	seasonally adjusted	Correlation between $MEANABSFE_{i,t}^{qual}$ and $STDFE_t^{qual}$ raw data	seasonally adjusted
Manufacturing	0.93	0.94	0.83	0.87
Industry				
Transport Equipment	0.92	0.90	0.59	0.58
Machinery and Equipment	0.94	0.94	0.75	0.75
Metal Products	0.92	0.92	0.62	0.62
Other non-metallic Products	0.90	0.90	0.71	0.71
Rubber and Plastic	0.85	0.85	0.59	0.66
Chemical Products	0.88	0.89	0.57	0.64
Elect. and Opt. Equipment	0.95	0.95	0.71	0.76
Paper and Publishing	0.91	0.91	0.72	0.76
Furniture and Jewelery	0.89	0.90	0.52	0.63
Cork and Wood Products	0.93	0.93	0.65	0.70
Leather	0.91	0.91	0.44	0.48
Textile Products	0.93	0.93	0.66	0.66
Food and Tobacco	0.89	0.88	0.74	0.78
Firm Size				
less than 50 employees	0.94	0.94	0.80	0.85
between 50 and 199 employees	0.93	0.92	0.79	0.83
between 200 and 499 employees	0.94	0.94	0.77	0.79
between 500 and 999 employees	0.94	0.95	0.74	0.75
more than 999	0.94	0.94	0.69	0.72

Notes: This table provides in the first two columns time-series correlation coefficients between $MEANABSFE$ and $FEDISP$ for specific groups of firms i with similar firm level characteristics, i.e., firm size and industrial affiliation. In the last two columns we do the same for $MEANABSFE$ and $STDFE$. Correlation coefficients are computed for the raw data as well as for the seasonally adjusted time series. We leave out the oil industry, since they have only very few observations. Numbers are provided for the qualitative definition of the expectation error. The construction of $MEANABSFE$, $FEDISP$ and $STDFE$ is explained in Section 2.

B Description of the Input Cost Variable

To compute a proxy for the cost of input goods, $\text{Costs}_{k,t}$ in sector k, we follow the approach outlined in Schenkelberg (forthcoming). In this approach, a weighted price variable of all sectors K that provide input goods for each production sector k is computed. This procedure follows three steps. First, we compute the weights of inputs for each sector k. To this end, we use data from input-output tables from the German Statistical Office. This data provides for each sector k the cost of input goods from each sector l (including from its own sector). Data is available for the years 1995 to 2007. For each year we calculate the cost share of the respective sector l used in the production process of sector k. Finally, we average these shares across time. Second, from the IFO-BCS we know whether a firm i from sector l changes its price in period t. We compute the net balance of price changes within a given sector l for each period t. That is, we subtract all price decrease from all price increases. We, therefore, need to assume that price increases (decreases) are similar across different firms within a sector. This gives us a proxy of the price of input goods from sector l. Third, we combine the weights of input goods from sector l in the production in sector k (from step one) with the respective price of goods from sector l at period t (from step two). The resulting time series is a proxy for input costs which sector k faces for each time period t.

To check our procedure we calculate a different proxy for input costs based on producer prices, $\text{Costs}_{k,t}^{ppi}$, which the German Federal Statistical Office publishes for all sectors. The problem with this in principle superior measure is that the data are only consistently available since 1995 on. We proceed as above. We compute the quarterly inflation rates of the producer prices for each sector k. We combine the weights of input goods form sector l in the production process in sector k with the respective producer prices inflation rate from sector l. We get a time series of input costs for each sector k for each time period. Time series correlation coefficients between $\text{Costs}_{k,t}$ and $\text{Costs}_{k,t}^{ppi}$ for the period of overlap are shown in Table 13. In almost all sectors we find high correlations which lends credence to the use of $\text{Costs}_{k,t}$ since producer prices at sectoral level are not fully available before 1995.

Table 13: Time Series Correlation Coefficients of Input Costs for Each Sector

Industry	Correlation between $\text{Costs}_{k,t}$ and $\text{Costs}_{k,t}^{ppi}$
Transport Equipment	0.74
Machinery and Equipment	0.67
Metal Products	0.65
Other non-metallic Products	0.77
Rubber and Plastic	0.68
Chemical Products	0.37
Elect. and Opt. Equipment	0.33
Paper and Publishing	0.38
Furniture and Jewelry	0.87
Cork and Wood Products	0.90
Leather	0.58
Textile Products	0.74
Food and Tobacco	0.51

Notes: This table provides correlation coefficients at the firm level between the input cost measure calculated with IFO-BCS net price balances, $\text{Costs}_{k,t}$, and the input cost measure based on sectoral producer price data, $\text{Costs}_{k,t}^{ppi}$. Sectoral producer price data are only fully available since 1995. The oil industry is omitted due to very few observations.

C Asymmetric Price Responses

Higher volatility increases the probability of price adjustments as we have shown in the main text body. In this appendix, we investigate whether this is also reflected in higher probabilities of both price increases and price decreases. The two price variables are calculated in the following way: If firm i states at date t that it increased (decreased) its price the dependent variable $Price\ increase_{i,t}$ ($Price\ decrease_{i,t}$) takes the value one, and zero otherwise.

We then estimate probit models in the spirit of the estimations in the main part of the paper, with the corresponding price increase and price decrease variables as dependent variables. We focus on $ABSFE^{qual}$ and $STDFE^{qual}$ as only these volatility measures are available at the monthly frequency. We use a specification at the monthly frequency because this makes the definition of a price increase and a price decrease unambiguous. The results are presented in Table 14. Heightened volatility increases the probability of both price increases and price decreases. This is another indication that the volatility effect dominates the wait-and-see effect. That is, price changes are more dispersed in times of higher volatility.

Table 14: Pooled Probit Model with Price Increase/Decrease (monthly model)

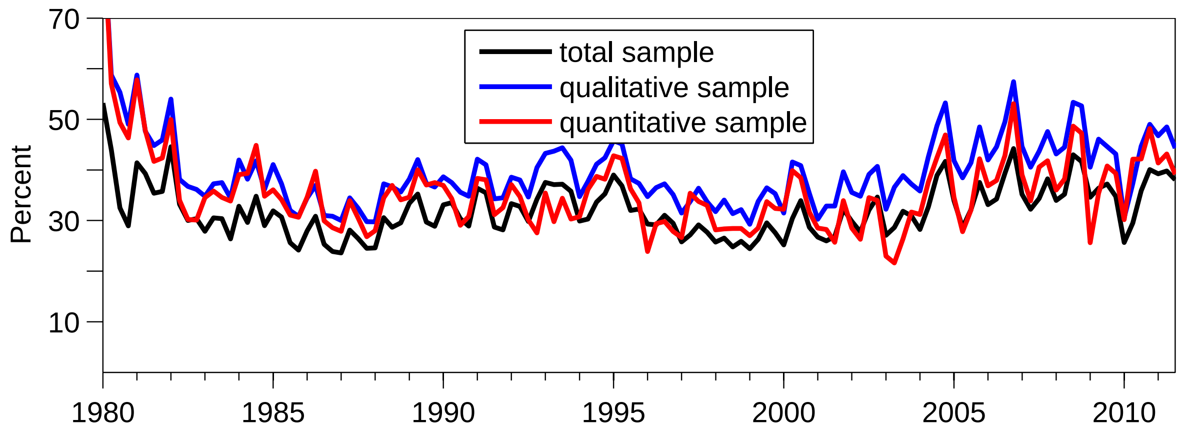
	(1)	(2)	(3)	(4)
Dependent variable: Price increase				
ABSFE^{qual}	0.002		0.002***	
	(0.001)		(0.001)	
STDFE^{qual}		0.001		0.003**
		(0.002)		(0.001)
Dependent variable: Price decrease				
ABSFE^{qual}	0.001***		0.001***	
	(0.000)		(0.000)	
STDFE^{qual}		0.001***		0.002***
		(0.000)		(0.001)
Observations	756,814	634,235	750,623	185,400

*** p<0.01, ** p<0.05, * p<0.1

Notes: The table presents marginal effects. Robust and clustered (by firm) standard errors are in parentheses. Included in the pooled probit model but not shown in the table are time-fixed effects for each month, sector-specific dummies, and Taylor dummies. Models (3)-(4) include, in addition, all firm-specific variables described in table 5. Taylor dummies are defined with respect to the last *month* in which a firm resets its price, e.g., $Taylor2$ takes a value of one if the last time a firm adjusted its price was two months ago. As in the quarterly specifications, we include two years worth of Taylor dummies. $ABSFE^{qual}$: qualitative idiosyncratic volatility; $STDFE^{qual}$: 5-quarter rolling window standard deviation of a firm's qualitative expectation errors.

D Comparison of Price Change Variables

Figure 4: Comparison of price change variables



Notes: The figure compares the (seasonally adjusted) frequency of price changes in the total sample, i.e., the raw data, the sample for which we construct qualitative volatility measures, and the sample for which we can compute quantitative volatility measures.