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TIME-VARYING BUSINESS VOLATILITY AND THE PRICE SETTING OF FIRMS

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ABSTRACT

Does time-varying business uncertainty/volatility affect the price setting of firms and, if so, in what way? 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 extensive margin of the price setting behavior of firms. We find that heightened business uncertainty increases the probability of a price change, which suggests that, for price setting, the volatility effect dominates the “wait-and-see” effect of uncertainty. In a second step, we use structural VAR models to estimate the effects of time-varying business uncertainty on the intensive pricing margin. We find that higher business uncertainty leads to both an increase in price dispersion and in the average size of absolute price changes which is mainly driven by price decreases. Taken together, our results show that higher business uncertainty causes a rise in both the extensive and intensive margins of price setting.

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1 Introduction

What are the effects of time-varying business (i.e., firm-level) uncertainty/volatility on the price setting behavior of firms?[1] As idiosyncratic volatility shocks have recently been shown to be important for replicating stylized business cycle facts of U.S. consumer price data (Vavra, 2014), it is important to know for the modeling of inflation dynamics if and in which direction volatility shocks affect the probability and size of price adjustments. Furthermore, a possible change in effective price flexibility due to high volatility, particularly in recessions, could affect the efficacy of macroeconomic stabilization policy.

In menu cost price setting models à la Vavra (2014), heightened business volatility can have (at least) two effects. First, to the extend that volatility also constitutes uncertainty for firms and adjusting prices is subject to at least some fixed costs, firms may want to "wait and see", refrain from adjusting their prices, and, thus, prices might become endogenously more sticky, when volatility is high. Second, higher volatility makes price adjustment of firms more likely as firms on average are hit by larger shocks. Hence, the sign of the relationship between firm-level volatility and the likelihood of price adjustment is an empirical question which has thus far not been studied in the literature.

Against this backdrop the contribution of our paper is twofold. First, based on firm-specific production expectation errors from the micro data of the West German manufacturing part of the ifo Business Climate Survey, we use their absolute values as well as rolling-window standard deviations as proxies for idiosyncratic business volatility. We then show empirically that idiosyncratic firm-level volatility is a statistically significant determinant of a firm's decision to reset its price (extensive margin),[2] with the volatility effect dominating the "wait-and-see" effect. This means that in times of high volatility, the price adjustment frequency in the economy, i.e., the share of firms adjusting their prices in a given period, increases.

[1]Strictly speaking, volatility is realized uncertainty, that is, "uncertainty" can be thought of as an ex-ante concept, while "volatility" is an ex-post one. Because of the lack of suitable ex-ante uncertainty data, in this paper we make use of ex-post forecast errors as proxies, which can be justified by a "stochastic volatility"-view of the world, where volatility has some persistence, and, thus, volatility in one period means volatility and uncertainty in close-by periods. Since, empirically, our results appear to be driven by effects coming from realized uncertainty, i.e., volatility, we will mostly use "volatility" for "uncertainty/volatility" in this paper, except where the distinction is relevant for the argument.

[2]We follow Klenow and Kryvtsov (2008) in defining the terms intensive and extensive margin. The extensive margin equals the frequency of price changes and the intensive margin defines the average size of (nonzero) price changes. In contrast to this, Caballero and Engel (2007) and Vavra (2014) use a different definition as they are interested in the change of inflation due to a first-moment aggregate shock. In their studies, the extensive margin describes the additional inflation coming from the rise in the fraction of agents adjusting upwards and the fall in the fraction of agents adjusting downwards, both as a result of an inflationary monetary policy shock. In this case, the extensive margin measures a compositional change in price adjusters. The intensive margin describes the additional price increase (or reduced price decrease) of those firms that would adjust their prices anyway.

While we highlight our qualitative result – the volatility effect dominates the "wait-and-see" effect in pricing –, we also provide a quantitative estimate of the elasticity between uncertainty/volatility and the frequency of price adjustment: prices are about 0.1 percentage points more likely to change when volatility increases by one percentage point. As a rough estimate of the quantitative magnitude of the net effect, this entails that increased business volatility can explain 0.65 percentage points of the 7 percentage points increase in the price adjustment frequency of West-German manufacturing firms during the 2008/09-recession. Second, we provide evidence that heightened firm-level volatility also leads to larger price adjustments (intensive margin) and to an increase in price dispersion. Perhaps interestingly, the adjustment along the intensive margin is mainly driven by firms that decrease their prices after an increase in business volatility. We also see this reflected in the fall in the aggregate price level following a business volatility shock. Conversely, conditional on an upward price adjustment after an increase in business volatility, it is mainly the extensive margin that operates, perhaps suggesting that firms follow a routine pricing rule conditional on upward adjustment. Conditional on downward price adjustment after an increase in business volatility, we see, by contrast, both the extensive and the intensive margins of price adjustment active.

While there have been earlier contributions (e.g., Bernanke, 1983; Brainard, 1967), the impact of volatility and uncertainty on the macroeconomy and macroeconomic policy-making has gained renewed attention in macroeconomic research since the beginning of the financial crisis. Starting with Bloom (2009), a part of this still growing literature has looked at the interaction of uncertainty and investment decisions of firms, where the propagation mechanisms discussed are physical adjustment frictions (e.g., Bachmann and Bayer, 2013, 2014; Bloom, 2009; Bloom et al., 2016), financial frictions (e.g., Arellano et al., 2016; Christiano et al., 2014; Gilchrist et al., 2014), or agency problems within production units (e.g., Narita, 2011; Panousi and Papanikolaou, 2012). Another part of this literature studies the macroeconomic effects of interest rate volatility (e.g., Fernández-Villaverde et al., 2011), fiscal policy volatility (e.g., Baker et al., 2016; Born and Pfeifer, 2014; Fernández-Villaverde et al., 2015), or general macroeconomic and financial uncertainty (e.g., Basu and Bundick, 2017; Berger et al., 2017; Jurado et al., 2015; Leduc and Liu, 2016; Ludvigson et al., 2015).

The consequences of heightened volatility for the price setting decisions of firms, however, have remained largely unexplored. Vavra (2014), 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.[3] Analyzing the importance of

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

"wait-and-see" and volatility effects, he also shows that, for his model and calibration, the volatility effect dominates. Vavra (2014), however, shows no direct empirical evidence that higher volatility leads to increases in the price adjustment frequency and price dispersion. Moreover, in a recent contribution, Baley and Blanco (2017) build a pricing model where endogenous uncertainty/volatility is generated by an information friction about productivity at the firm level and learning. The authors show that an increase in uncertainty makes firms learn more, makes them more responsive to new (noisy) information, and, hence, leads them to adjust their prices more frequently.[4] Our paper provides empirical support for the theoretical predictions from Vavra (2014), Baley and Blanco (2017), and the rational inattention literature.

The novel contribution of this paper is to use measures of firm-specific volatility to estimate and quantify directly the impact of heightened firm-level volatility on the firms' price setting behavior. These business volatility measures are constructed from the confidential micro data in the ifo Business Climate Survey. 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 capture *uncertainty at the firm level*, and thus allow the "wait-and-see" effect caused by uncertainty to have a chance 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 nondisclosure agreements. The unique feature of the German ifo Business Climate Survey is that it allows us to construct for the same firms firm-specific volatility measures and use information on their price setting behavior. It also allows us to use a rich set of firm-level covariates to help us isolate the effect of volatility on firms' price setting.

We use two strategies to construct the firm-specific volatility measures. The first one follows Bachmann et al. (2013) and Bachmann and Elstner (2015). Bachmann et al. (2013) construct production expectation errors at the firm level, based on qualitative survey questions regarding expected and realized production changes at the firm level. We use the absolute value of these expectation errors as one of our measures of idiosyncratic volatility. The advantage of this qualitative measure is that it can be constructed for a relatively large sample of firms. However, qualitative measures only allow us to evaluate *the sign* of the relationship between volatility and price setting at the firm level. Therefore, making additional assumptions, we compute for a subset of firms a quantitative volatility measure in line with Bachmann and Elstner (2015) from firm statements about capacity utilization.

[4] This result is also in line with Maćkowiak and Wiederholt (2009, 2015), who find that in "rational inattention"-environments more volatility leads to more frequent updating of prices.

The second strategy is based on the same qualitative and quantitative expectation errors but, instead of the absolute expectation error, relies on a firm-specific rolling window standard deviation as in Comin and Mulani (2006) and Davis et al. (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 then estimate a probit model on a panel of (on average) 2,500 German firms from January 1980 to December 2015.

The qualitative price data in the ifo survey, however, do not allow us to analyze whether uncertain firms change their prices by smaller or larger amounts than less uncertain firms (intensive margin). To study these effects we use highly confidential quantitative price data of the German Federal Statistical Office that are underlying the German producer price index (PPI). Unfortunately, we only have access to this data since 2005 due to institutional reasons. We also cannot match the PPI micro data to the ifo survey data, so we have no measures of firm-specific volatility in the PPI data, which makes firm-level regressions infeasible. We thus base our analysis on structural vector autoregressions (SVARs) that include our measures of firm-level volatility, aggregated up, and quantitative micro pricing moments, in addition to a set of variables controlling for forward-looking information as well as demand and cost developments. Identifying exogenous uncertainty/volatility shocks in the standard recursive way (Bloom, 2009; Jurado et al., 2015), this empirical framework allows us to analyze the dynamics of the intensive margin after exogenous changes in firm-level volatility.

The remainder of this paper is structured as follows. The next section describes the ifo survey data 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 idiosyncratic business volatility on the price setting of firms. We provide a number of robustness checks in Section 4. Section 5 presents the PPI micro data of the Federal Statistical Office and discusses the SVAR results. The last section concludes.

2 Measuring idiosyncratic volatility

In this section, we describe the construction of idiosyncratic volatility measures from ifo Business Climate Survey (henceforth ifo) data.

2.1 ifo Business Climate Survey

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
Q11	*Financial Constraints*	How do you evaluate the current willingness of banks to grant credits to businesses?	accommodating	normal	restrictive

Notes: This table provides the translated questions and response possibilities of the ifo survey for manufacturing. For the production questions Q1 and Q2, firms are explicitly asked to ignore differences in the length of months or seasonal fluctuations. For Q8, customary full utilization is defined by 100%. Q11 has been introduced in 2003 and was posed until November 2008 twice a year in March and August. Afterwards it has become a regular item of the monthly 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), and, since then, its survey design 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 2015 (IBS-IND, 2016). Our analysis excludes East German firms.

An attractive feature of the ifo survey is the relatively high number of participants. The average number of respondents at the beginning of our sample is approximately 5,000 per wave; towards the end, it declines to 2,000.[5] 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. The ifo attempts to maintain a sample that is representative of the German manufacturing sector by replacing exiting firms with new respondents.

The ifo survey, at 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.

2.2 Construction of qualitative volatility 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 survey, 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:[6] 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 survey 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

[5] The ifo survey 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.

[6] 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		
Expect. in $\tau-1$	*Increase*	*Unchanged*	*Decrease*
Increase	0	-1	-2
Unchanged	+1	0	-1
Decrease	+2	+1	0

Notes: Rows: past production change expectations; columns: current production change realizations.

between $\tau-2$ and $\tau-1$, and production decreased between $\tau-1$ and τ. Due to the qualitative nature of the ifo data 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 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)

Expect. in $\tau-3$	$REALIZ_{i,\tau}$	$FE^{qual}_{i,\tau}$
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 survey (Q2) in month $\tau-3$.

Notice that the procedure in Table 3 is analogous to the one month case. Our final expectation error $FE^{qual}_{i,\tau}$ 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 $FE^{qual}_{i,\tau+3}$ as a measure of idiosyncratic volatility in period τ of firm

i.[7] We denote this variable by $ABSFE^{qual}_{i,\tau}$:

$$ABSFE^{qual}_{i,\tau} = \left| FE^{qual}_{i,\tau+3} \right| \ . \tag{1}$$

With this timing, we assume that firms essentially know the size of their forecast error in $\tau + 3$, if not its sign, and use this information to make pricing decisions in τ, under this known level of uncertainty. Independently of what we believe about the realism of this assumption, we contend that it maximizes the chances of a pure uncertainty "wait-and-see" effect to shine through, because we do not use (the absolute value of) forecast errors and thus realized volatility from period τ. For a further discussion of this timing assumption as regards uncertainty, see Bachmann and Bayer (2013).[8]

We also compute a measure of firm-level volatility based on Comin and Mulani (2006) and Davis et al. (2006). Using a firm i's expectation errors we can define a symmetric 3-quarter rolling window standard deviation as

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

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

2.3 Construction of quantitative volatility measures

Bachmann and Elstner (2015) argue that the supplementary question about capacity utilization (Q8) permits – under certain assumptions – the construction of quantitative production expectations. To illustrate this, we start from the following production relationship of an individual firm i:

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

where $y^{act}_{i,\tau}$ denotes the firm's actual output, $y^{pot}_{i,\tau}$ its potential output level, and $u_{i,\tau}$ the level of capacity utilization. Only $u_{i,\tau}$ is directly observable in the ifo data. Taking the natural

[7] The use of the absolute forecast error as a volatility proxy is motivated by the stochastic volatility model (see, e.g., Fernández-Villaverde et al., 2010, 2011; Shephard, 2008). In this model, given the level equation $y_t = f(y_{t-1}, y_{t-2,\dots}) + e^{\sigma_t}\nu_t$, where $f(y_{t-1}, y_{t-2,\dots})$ is some function of the lags of y_t, the time-varying log standard deviation evolves according to $\sigma_t = (1-\rho)\,\bar{\sigma} + \rho\sigma_{t-1} + \eta\varepsilon_t$, where ε_t is an i.i.d. volatility innovation, often distributed as standard normal. The forecast error is then given by $e^{\sigma_t}\nu_t$, where the level shock ν_t is independent of ε_t. The higher the relative importance of volatility shocks ε_t compared to level shocks ν_t, the closer are volatility and absolute forecast error linked. In the extreme case of ν_t only having realizations -1 or $+1$, e^{σ_t} and $|e^{\sigma_t}\nu_t|$ coincide.

[8] We also vary this timing assumption in the robustness checks.

logarithm and the three-month difference, we get[9]

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

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.[10] 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, and 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 in the baseline specification 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.[11] 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 $FE_{i,\tau}^{quan}$.[12]

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

[10] It should be clear that the volatility proxies that we can derive from this procedure refer to any shock process that affects production, but leaves the potential output of a firm unchanged.

[11] 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 "potentially 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 potentially inconsistent when 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 potentially inconsistent. In our sample we have 420,507 firm-level observations for $u_{i,\tau}$. The number of outliers is quite small and corresponds to 245 observations. With the remaining observations we are able to compute 377,010 changes in capacity utilization, $\Delta \log u_{i,\tau}$. For 196,929 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 79,027 observations as "potentially inconsistent" and drop them. Our final sample consists of 117,902 observations for $\Delta y_{i,\tau}^{act}$. Bachmann and Elstner (2015) argue that this sample does not appear to be specifically selected on observables. We also deal with the sample design in our robustness checks.

[12] Firms are asked about their capacity utilization in March, June, September, and December, allowing

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, however at the cost of smaller samples and additional assumptions, which is why we emphasize in particular our qualitative result, namely that the volatility effect dominates the "wait-and-see" effect in price setting.

We also compute a 3-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 75% compared to the sample size for $ABSFE^{quan}_{i,\tau}$, because we need to observe a firm's quantitative expectation error three times in a row.

2.4 Discussion of volatility measures

How do our measures of idiosyncratic volatility 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., $\overline{ABSFE}^{qual}_{\tau}$, and the cross-sectional dispersion of expectation errors (see Bachmann et al., 2013) defined as

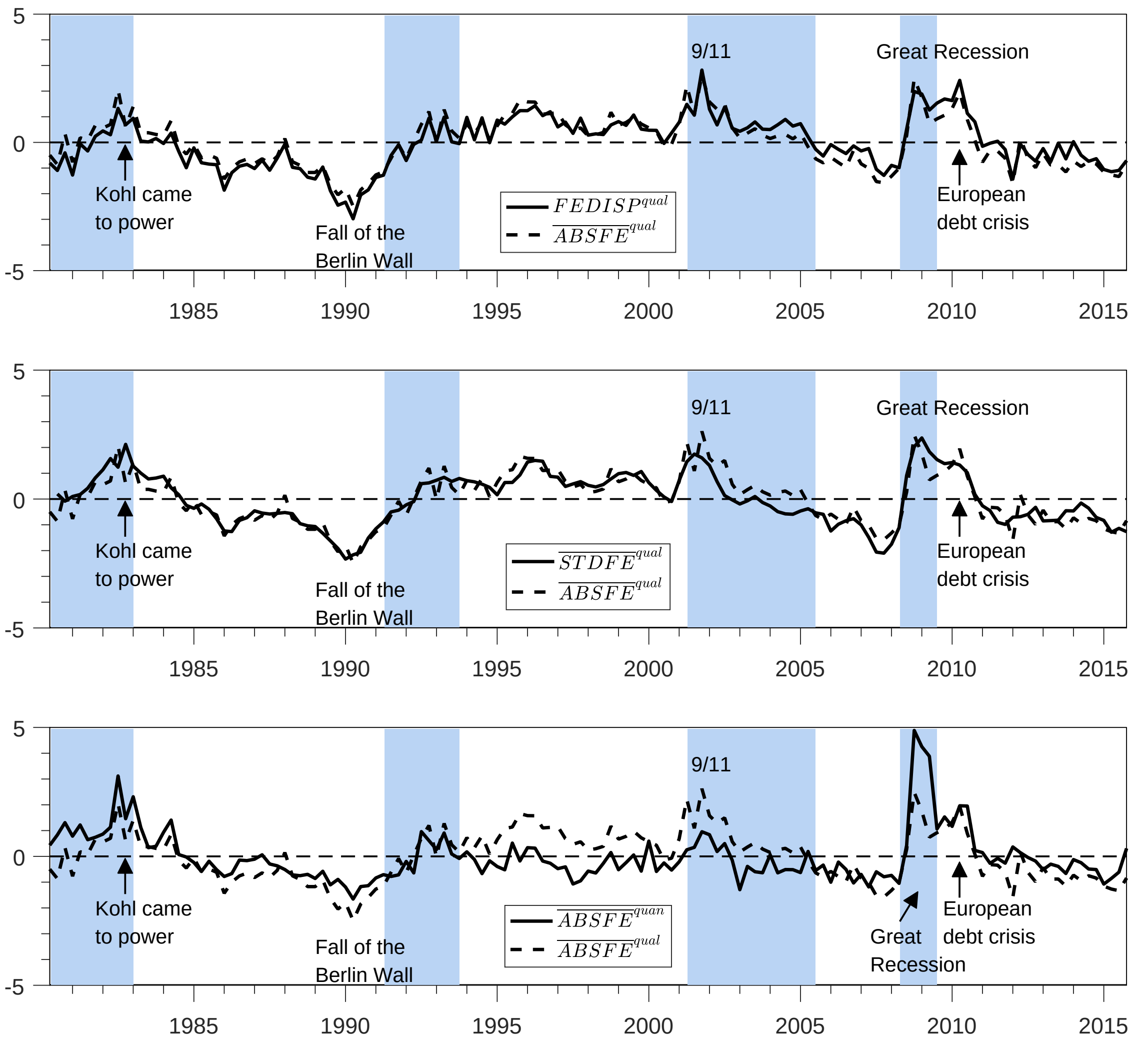
$$FEDISP^{qual}_{\tau} = \text{std}\left(FE^{qual}_{i,\tau+3}\right). \tag{6}$$

Both time series display similar properties:[13] they rise in the wake of the fall of the Berlin Wall – a clear turning point in the evolution of volatility following the calm 1980s, again around 2001, and at the start of the global financial crisis, where they remain elevated with the onset of the European debt crisis. Overall, 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 $\overline{ABSFE}^{qual}_{\tau}$.

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 to be able to better compare the results from both frameworks. As robustness checks, we also run regressions using the (larger) monthly qualitative sample.

[13]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.

Figure 1: Measures of idiosyncratic volatility



Notes: Upper panel: quarterly time series of the average absolute forecast errors, $\overline{ABSFE}_{\tau}^{qual}$, and of the cross-sectional standard deviation of forecast errors, $FEDISP_{\tau}^{qual}$; middle panel: quarterly time series of the average absolute forecast errors, $\overline{ABSFE}_{\tau}^{qual}$, and of the average 3-quarter rolling window standard deviation, $\overline{STDFE}_{\tau}^{qual}$; lower panel: quarterly values of the average absolute qualitative forecast errors, $\overline{ABSFE}_{\tau}^{qual}$, and the average absolute quantitative forecast errors, $\overline{ABSFE}_{\tau}^{quan}$. Forecast errors are ex-ante, i.e., timed at the date of the forecast. Monthly series are transformed to the quarterly frequency by selecting the last month of each quarter. The sample period is 1980q1-2015q4. Each series has been demeaned and standardized by its standard deviation and seasonally adjusted. Shaded regions denote recessions as dated by the German Council of Economic Experts (GCEE): 1980q1-1982q4, 1991q1-1993q3, 2001q1-2005q2, and 2008q1-2009q2.

The middle panel of Figure 1 shows the cross-sectional mean of $STDFE_{i,\tau}^{qual}$, i.e., $\overline{STDFE}_{\tau}^{qual}$, together with $\overline{ABSFE}_{\tau}^{qual}$. Both time series comove closely with a high positive time-series correlation coefficient of 0.89. This relationship also holds at the firm level: here we find a Spearman correlation coefficient between $ABSFE_{i,\tau}^{qual}$ and $STDFE_{i,\tau}^{qual}$ of 0.52.[14] The strong comovement between $FEDISP_{\tau}^{qual}$, $\overline{ABSFE}_{\tau}^{qual}$, and $\overline{STDFE}_{\tau}^{qual}$ shows that, at least in an average sense, large absolute forecast errors at the firm level are not simply the result of mere one-off wrongness of individual firms about their forecasts, but rather the result of heteroskedasticity, i.e., of time-varying distributions.

The link between qualitative and quantitative absolute expectation errors is illustrated in the lower panel of Figure 1, where we plot the cross-sectional mean of $ABSFE_{i,\tau}^{quan}$ ($\overline{ABSFE}_{\tau}^{quan}$) together with $\overline{ABSFE}_{\tau}^{qual}$. Both measures of idiosyncratic volatility move again close to each other. The unconditional time-series correlation coefficient between $\overline{ABSFE}_{\tau}^{quan}$ and $\overline{ABSFE}_{\tau}^{qual}$ is 0.61. At the firm level we find a pooled Spearman correlation coefficient between $ABSFE_{i,\tau}^{qual}$ and $ABSFE_{i,\tau}^{quan}$ of 0.65. $\overline{ABSFE}_{\tau}^{quan}$ is also positively correlated with $\overline{STDFE}_{\tau}^{quan}$ and $FEDISP_{\tau}^{qual}$ (see Table 4).

Table 4 also shows that, at an aggregate level, the correlation between our volatility measures and macroeconomic uncertainty à la Jurado et al. (2015) is positive and statistically significant.[15]

Looking at business cycle properties, all of our volatility measures are countercyclical: their unconditional pairwise time-series correlation coefficients with quarter-to-quarter growth rates of real production, total hours worked, and employment in the West-German manufacturing sector are negative (see Table 4). We also find for all volatility measures that they are larger in recession times, e.g., $\overline{ABSFE}^{quan}$ increases by about one percentage point in times of economic slack. For the last recession, starting in 2008q1 and ending in 2009q2, $\overline{ABSFE}^{quan}$ even increased by roughly three percentage points compared to non-recession times.[16] For all qualitative volatility measures, we present in Table 4 the time-series averages as a ratio to the non-recession mean, implying that for example $FEDISP^{qual}$ rises on average by 3.3 percent in times of recessions.

Further evidence for the appropriateness of our measures comes from disaggregating the time series and analyzing the time-series correlation coefficients for 13 manufacturing

[14]For the quantitative expectation errors, we find a Pearson correlation coefficient between $ABSFE_{i,\tau}^{quan}$ and $STDFE_{i,\tau}^{quan}$ of 0.75.

[15]For the latter series, we use the macroeconomic uncertainty series for Germany provided by Meinen and Röhe (2017), which is constructed following Jurado et al. (2015). Specifically, we use their series for a three-month forecast horizon (h=3) which corresponds most closely to the horizon of our measures.

[16]To get an upper bound of the volatility increase during the Great Recession, we can take the peak of $ABSFE^{quan}$ in the second half of 2008 and set it in relation to the mean in the last non-recession year 2007, yielding an increase of 6.5 percentage points.

Table 4: Cross-correlations of real activity and volatility measures

	$FEDISP^{qual}$	$\overline{ABSFE}^{qual}$	$\overline{STDFE}^{qual}$	$\overline{ABSFE}^{quan}$	$\overline{STDFE}^{quan}$
Correlation coefficients					
$\Delta \log Production$	-0.21**	-0.25***	-0.34***	-0.44**	-0.25***
$\Delta \log Hours$	-0.26***	-0.32***	-0.38***	-0.25**	-0.26***
$\Delta \log Employment$	-0.44***	-0.48***	-0.50***	-0.28***	-0.31***
Macro Uncertainty	0.59***	0.58***	0.65***	0.76***	0.51***
$FEDISP^{qual}$	1.00	0.94***	0.83***	0.56***	0.22**
$\overline{ABSFE}^{qual}$		1.00	0.89***	0.61***	0.43***
$\overline{STDFE}^{qual}$			1.00	0.68***	0.55***
$\overline{ABSFE}^{quan}$				1.00	0.53***
$\overline{STDFE}^{quan}$					1.00
Business cycle properties					
Non-recess. mean	1.000	1.000	1.000	0.045	0.019
Recess. mean	1.033	1.065	1.054	0.055	0.023
Recess. 2008/09 mean	1.062	1.095	1.112	0.075	0.026
Coeff. of var.	0.049	0.084	0.073	0.252	0.375

Notes: Upper panel: pairwise unconditional time-series correlation coefficients of firm-level volatility measures with West-German economic activity and an aggregate uncertainty measure; lower panel: means of firm-level volatility measures for non-recession and recession periods and the coefficient of variation of these proxies. To compute the mean of the qualitative volatility measures, we first standardize the original time series by their non-recession means. The corresponding means for the non-recessions periods are therefore one. Monthly qualitative volatility measures are transformed to quarterly frequency by selecting the last month of each quarter, even for those correlations that only involve qualitative volatility measures. Economic activity variables are quarter-on-quarter growth of real production ($\Delta \log Production$), total hours worked ($\Delta \log Hours$), and employment ($\Delta \log Employment$). For macroeconomic uncertainty, we use data provided by Meinen and Röhe (2017) which start in 1996q3 (forecast horizon: h=3). For all other variables, the sample period is 1980q1 - 2015q4. All variables are seasonally adjusted. Recessions are as dated by GCEE (see notes to Figure 1). To test for significance of the time-series correlations (in a one-sided test) we use a nonparametric overlapping bootstrap with a four-quarter window and 10,000 replications. *** denotes 1% significance, ** 5% significance, and * 10% significance.

industries and 5 firm-size classes separately. The results are summarized in Table 18 in Appendix A. Columns 2 and 3 report correlations for $\overline{ABSFE}_{\tau}^{qual}$ and $FEDISP_{\tau}^{qual}$. All industries and firm-size classes feature correlation coefficients that are around 0.9 or higher. The last two columns compare $\overline{ABSFE}_{\tau}^{qual}$ and $\overline{STDFE}_{\tau}^{qual}$. Here, the strength of the association 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 firm volatility on the frequency of price adjustment. We first specify the empirical model and then present the results.

3.1 Construction of price variables

Table 5: Business cycle properties of frequency of price changes

Dependent variable: share of price changes		
	manufacturing	retail
Non-recession mean	0.303***	0.440***
	(0.004)	(0.008)
Recession dummy	0.031***	0.038***
	(0.008)	(0.014)
2008/09 recession dummy	0.049***	0.047
	(0.018)	(0.029)
Mean of dep. var.	0.316	0.455
Std. of dep. var.	0.052	0.069
Observations	144	104
Adj. R-squared	0.180	0.107

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

Notes: Each column presents the results of a regression of the quarterly share of price changes on a constant, a general recession dummy, and a 2008/09-recession dummy (with standard errors in parentheses). All data are seasonally adjusted using quarterly dummies. The manufacturing sample is based on the survey of West-German manufacturing firms and spans the period 1980q1-2015q4, while the retail sample is based on a survey of West-German retail firms and is available for the period 1990q1-2015q4. Recessions are as dated by the GCEE (see notes to Figure 1).

Although the ifo data include 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.[17]

The manufacturing column of Table 5 provides evidence for the countercyclicality of the frequency of price changes. Here, we regress the seasonally adjusted share of price changes in a given quarter on a constant and a recession dummy. On average, the frequency of price changes is significantly higher in recessions (33.4%) than in normal times (30.3%), and especially so in the 2008/09 recession. We further find that the frequency of price changes

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

has a time-series standard deviation of 5.2 percentage points. Both numbers will help us put our estimation results into perspective.[18]

The price statements that underlie our results are conceptually close to the producer price index (PPI), because they come from manufacturing firms. While the ifo has data for retail firms that would be conceptually closer to consumer prices, the retail micro data do not allow us to compute volatility proxies that are comparable to those of the manufacturing part of the survey. Nonetheless, it is instructive to compare the business cycle properties of the price setting in the two sectors, because, as it turns out, the frequency of price adjustment is also countercyclical in the retail sector. Due to data availability in the retail part of the survey, our sample only starts in 1990 (IBS-TRA, 2016). We find that retail firms have a higher probability to reset their prices: on average 45.5% of all retail firms adjust their prices each quarter compared to 31.6% in manufacturing. Even so, the frequency of price adjustment of the retail sector increases in recessions by 3.8 percentage points on average, an increase that is similar to the one in the manufacturing sector.[19] The countercyclicality of the price adjustment frequency is also what Vavra (2014) and Berger and Vavra (2016) find for U.S. CPI data.

3.2 The empirical model

As a baseline, we use a quarterly probit model[20]

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

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.

Table 6 lists the variables used in the estimation procedure. At the heart of the empirical analysis are the volatility measures described in Section 2. We use, each in turn, two qualitative volatility measures ($ABSFE^{qual}$ and $STDFE^{qual}$) and two quantitative ones ($ABSFE^{quan}$ and $STDFE^{quan}$). Taylor dummies ($Taylor1$ - $Taylor8$) 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. Industry dummies ($Industry1$ -

[18]In Section 5, Table 17, we compare the ifo pricing data to the micro data underlying the overall producer price index provided by the German Federal Statistical Office and find that, in the aggregate, they correlate well and have similar business cycle properties.

[19]At the *monthly* frequency, we find for the ifo manufacturing (retail) data an average price change frequency of 17.4% (27.6%). During recessions the monthly frequency of price adjustment is 1.8 percentage points (3.7 percentage points) higher than in non-recessions.

[20]We also estimated logit models with essentially the same results.

$Industry14$) account for unobserved heterogeneity between manufacturing industries. 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.

Table 6: Variable description

Label	Variable	Response	Scale
Taylor dummies	$Taylor1 - Taylor8$		Binary
Industry dummies	$Industry1 - Industry14$		Binary
Time-fixed effects	$Time1\ldots$		Binary
Capacity Utilization	*Capacity utiliz.*	30%, 40%...70%, 75%, 80%...100%...	Interval
Cost of Input Goods	$\Delta Costs$	$-0.42\ldots0.87$	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
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

One of the advantages of the ifo data is that it includes many firm-specific variables that allow us to control for first-moment effects. *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*.[21] *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. The idea is that heightened uncertainty may lead to the postponement of projects in other firms, which would decrease the demand for certain goods in the economy.

[21] 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.

Changes in input costs are included to capture supply shocks. Lein (2010) emphasizes the important role of intermediate good costs as a determinant of a firm's price setting. The ifo dataset 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 manufacturing industry k for each time period ($\Delta Costs_{k,t}$) following Schenkelberg (2013). $\Delta Costs_{k,t}$ for each industry is calculated as the weighted average of net price changes of input goods from all industries. The weights are derived from the relative importance of the industries in the production of goods in industry k.[22]

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 $Statebus^{-}_{i,t}$ 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*.

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).

3.3 Baseline results

The estimation results of the baseline probit models with *Price change* as the dependent variable are presented in Table 7. The first four models – Columns (1) to (4) – include a constant and a set of industry, Taylor, and time-fixed effect dummies. The other four models – Columns (5) to (8) – contain, in addition, the set of firm-specific variables described in Table 6.[23] Each of the eight models includes one volatility measure. Models (1) and (5) use

[22]See Appendix B for a detailed description.

[23]Table 20 in Appendix C.1 shows the results for linear regression specifications with and without firm-fixed effects. The results are in line with the baseline although quantitatively somewhat smaller when including

Table 7: Results from the baseline probit model

Dependent variable: price change								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$ABSFE^{qual}$	0.014***				0.008***			
	(0.001)				(0.002)			
$ABSFE^{quan}$		0.116***				0.105***		
		(0.020)				(0.024)		
$STDFE^{qual}$			0.029***				0.013***	
			(0.002)				(0.002)	
$STDFE^{quan}$				0.188***				0.140**
				(0.063)				(0.063)
Capacity utiliz.					0.001***	0.001***	0.000***	0.001***
					(0.000)	(0.000)	(0.000)	(0.000)
Δ Costs					0.258***	0.351***	0.038**	0.108*
					(0.026)	(0.047)	(0.016)	(0.064)
$Statebus^{+}$					0.031***	0.037***	0.017***	0.031***
					(0.004)	(0.006)	(0.003)	(0.010)
$Statebus^{-}$					0.049***	0.066***	0.028***	0.064***
					(0.004)	(0.009)	(0.003)	(0.020)
$Expbus^{+}$					0.017***	0.018**	0.009***	0.025*
					(0.004)	(0.008)	(0.002)	(0.014)
$Expbus^{-}$					0.059***	0.045***	0.034***	0.009
					(0.004)	(0.008)	(0.003)	(0.012)
$Orders^{+}$					0.077***	0.063***	0.044***	0.039***
					(0.004)	(0.006)	(0.004)	(0.012)
$Orders^{-}$					0.063***	0.050***	0.033***	0.037***
					(0.004)	(0.006)	(0.003)	(0.011)
Tech. $capacity^{+}$					0.012***		0.007***	
					(0.004)		(0.002)	
Tech. $capacity^{-}$					0.052***		0.028***	
					(0.006)		(0.004)	
$Expempl^{+}$					0.029***		0.016***	
					(0.006)		(0.004)	
$Expempl^{-}$					0.031***		0.018***	
					(0.004)		(0.003)	
Observations	263,224	66,330	244,069	16,956	209,562	58,353	195,123	15,095
Pseudo R-squared	0.118	0.128	0.123	0.160	0.130	0.135	0.134	0.165

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

Notes: Table reports marginal effects; robust and clustered (by firm) standard errors in parentheses. Included in the probit model but not shown in the table are time-fixed effects for each quarter, industry-specific dummies, and Taylor dummies. Models (5) and (7) include, in addition, all firm-specific variables described in Table 6. Model (6) and (8) include the same firm-specific variables except *Technical Capacity* and *Expected Employees*. 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; $STDFE^{qual}$: 3-quarter rolling window standard deviation of a firm's qualitative expectation errors; $STDFE^{quan}$: 3-quarter rolling window standard deviation of a firm's quantitative expectation errors.

firm-fixed effects, which means that our results are not exclusively driven by fixed cross-sectional firm heterogeneity.

the absolute qualitative forecast error, $ABSFE^{qual}$, (2) and (6) the absolute quantitative forecast error, $ABSFE^{quan}$, (3) and (7) the 3-quarter rolling window standard deviation of firms' qualitative expectation errors, $STDFE^{qual}$, and (4) and (8) the 3-quarter rolling window standard deviation of firms' quantitative expectation errors, $STDFE^{quan}$.

The table reports marginal effects. Quantitative variables (*Capacity utiliz.*, Δ*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.

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 are associated with a higher probability of price change.

The main takeaway from Table 7 for our research question, however, 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, i.e., the volatility effect prevails over the "wait-and-see" effect. 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));[24] and the marginal effects for $ABSFE^{quan}$ imply that prices are about 0.1 percentage points more likely to change when $ABSFE^{quan}$ changes by one percentage point. Turning to the rolling window proxies, we find that the marginal effects for $STDFE^{qual}$ are also positive, as are the marginal effects for $STDFE^{quan}$.

Given that the association between business uncertainty/volatility and the frequency of price setting is positive, how then can volatility tomorrow induce such a positive volatility effect today? For the rolling window standard deviation, this can be explained by the fact that by construction it contains forecast errors from multiple periods, including today's. As for *ABSFE*, a stochastic volatility cum persistence view makes tomorrow's forecast error a good proxy of volatility today. We can test this by including lags of the absolute forecast error proxy in our baseline regression, which should also be good proxies of instantaneous volatility today. We find that indeed these lags considerably reduce the impact of our baseline forward-looking uncertainty/volatility proxy, i.e., the one based on tomorrow's forecast error, even rendering it statistically insignificant in some cases (see Table 8).

For a rough estimate of what the 0.1 percentage point marginal effect for $ABSFE^{quan}$

[24] There is little meaning in the *size* of the marginal effects of $ABSFE^{qual}$.

Table 8: Baseline probit with lagged volatility proxies

Dependent variable: price change								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$ABSFE_t^{qual}$	0.003***	0.002***			0.001**	0.001*		
	(0.001)	(0.001)			(0.001)	(0.001)		
$ABSFE_{t-1}^{qual}$	0.008***	0.007***			0.003***	0.003***		
	(0.001)	(0.001)			(0.001)	(0.001)		
$ABSFE_{t-2}^{qual}$		0.002***				0.001		
		(0.001)				(0.000)		
$ABSFE_t^{quan}$			0.028*	-0.053			0.013	-0.049
			(0.017)	(0.033)			(0.014)	(0.030)
$ABSFE_{t-1}^{quan}$			0.069***	0.084*			0.032*	0.044
			(0.023)	(0.043)			(0.018)	(0.035)
$ABSFE_{t-2}^{quan}$				0.004				0.006
				(0.042)				(0.037)
Observations	245,022	228,443	29,627	16,168	196,059	183,426	26,286	14,457
R-squared	0.159	0.167	0.173	0.195	0.168	0.176	0.180	0.202

*** 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 probit model but not shown in the table are time-fixed effects for each quarter, industry-specific dummies, and Taylor dummies. Models (5) and (6) include, in addition, all firm-specific variables described in Table 6. Models (7) and (8) include the same firm-specific variables except *Technical Capacity* and *Expected Employees*. 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.

means, it is helpful to remember two numbers. We have seen in Table 5 that the price adjustment frequency of West-German manufacturing firms is 3.1 percentage points higher in recessions compared to non-recession periods. At the same time, in recessions, the cross-sectional average of $ABSFE^{quan}$ is roughly one percentage point higher than in normal times (see the lower panel of Table 4). So only a fraction of the increase in the price adjustment frequency can be explained by an increase in firm-level volatility.[25] Even if we take the difference of 6.5 percentage points between the peak of $ABSFE^{quan}$ in the second half of 2008 and its mean in the last non-recession year 2007 (see footnote 16), we would obtain an increase in the price adjustment frequency of 0.65 percentage points compared to the actual increase of seven percentage points during that time period.[26]

[25] We also check whether our estimated coefficients differ between recession and non-recession times by splitting our sample accordingly and running separate regressions. Table 21 in Appendix C.1 shows that the coefficients are fairly stable. We also run our baseline regression year by year and find mostly positive marginal effects which show no clear cyclical pattern; results are available on request.

[26] Of course, this calculation, based on the marginal effect estimated in a microeconometric procedure,

Summing up, we find that idiosyncratic volatility is a statistically significant, albeit not economically strong determinant of the price setting behavior of firms and that the volatility effect dominates the "wait-and-see" effect, i.e., higher volatility leads firms to adjust their prices more often.

To understand the anatomy of price changes after changes in business volatility better, we can make use of additional information in the ifo data, which provides also information on whether a firm increased or decreased its price.

While the definition of a price increase and decrease is straightforward at the monthly frequency, given the monthly frequency of the underlying data set, it is somewhat ambiguous at the quarterly frequency. We define the dependent variable as 1 (-1) if there is a price increase (decrease) in at least one of the three months but no decrease (increase). If we observe both an increase and decrease, we set the observation to missing. The dependent variable is only 0 if there is no price change in any of the three months.

Table 9: Multinomial logit model for price increases and decreases

	(1)	(2)	(1)	(2)
	$ABSFE^{qual}$		$ABSFE^{quan}$	
Priceup	0.006***	0.007***	-0.004	0.028
	(0.001)	(0.002)	(0.023)	(0.025)
Pricedown	0.004***	0.002***	0.058***	0.057***
	(0.000)	(0.001)	(0.011)	(0.014)
Observations	260,388	207,518	65,731	57,874
	$STDFE^{qual}$		$STDFE^{quan}$	
Priceup	0.008***	0.006***	0.046	0.029
	(0.001)	(0.001)	(0.037)	(0.029)
Pricedown	0.016***	0.006***	0.169**	0.200**
	(0.002)	(0.001)	(0.072)	(0.097)
Observations	241,625	193,346	16,828	14,987

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

Notes: Table reports marginal effects; robust and clustered (by firm) standard errors in parentheses. Included in the multinomial logit model but not shown in the table are time-fixed effects for each quarter, industry-specific dummies, and Taylor dummies. Model (2) includes, in addition, all firm-specific variables described in Table 6.

The first two columns of Table 9 show the results of estimating multinomial logit models for the qualitative volatility proxies. Heightened volatility increases significantly the probability of both price increases and price decreases.[27] The results for the quantitative volatility proxies

abstracts from all potential macro effects.

[27]The results in Table 9 are similar when we use an alternative aggregation scheme where we set observations to 0 if we observe both a price increase and decrease within a quarter. Furthermore, estimating the multinomial logit at the monthly frequency using only the qualitative volatility proxies yields very similar results to the

are roughly in line with those for the qualitative volatility proxies, albeit, for the case of price increases, not at conventional statistical significance levels. That price changes are more dispersed in times of higher volatility is in line with the results in Vavra (2014).

4 Robustness checks

The results from the baseline estimations show that the probability of price adjustment increases by about 0.1 percentage points when business volatility rises by one percentage point as measured by the absolute quantitative production expectation errors (see the sixth column in Table 7). We now conduct a battery of robustness checks that can be classified into three blocks: (i) the role of first-moment effects, (ii) potential measurement issues in the construction of the price and volatility variables, and (iii) the role of financial constraints.

4.1 The role of first-moment effects

In our baseline estimations, we control for various first-moment proxies, as can be seen in columns (5) to (8) of Table 7. This is potentially important as positive second-moment effects are often accompanied by negative first-moment effects (Bachmann and Bayer, 2013; Bloom et al., 2016). Is there, thus, still a possibility that we pick up first-moment effects in our baseline estimations; especially in those cases, where we use the absolute forecast error as our uncertainty/volatility proxy? As shown in equation (1), however, we calculate $ABSFE^{qual}$ and $ABSFE^{quan}$ for period t with the realized expectation error in period $t + 1$.[28] This is because with our baseline timing assumption – firms are uncertain today because today they expect a large shock tomorrow – we want to avoid using information on realized forecast errors today to give a pure uncertainty "wait-and-see" effect the best chance to emerge. At the same time, we also mitigate the danger that we are just picking up a large first-moment shock today, that is, one-time wrongness. Similarly, one-time wrongness is less likely to be picked up in those cases, where we use the rolling window standard deviation approach, $STDFE^{qual}$ and $STDFE^{quan}$. This is because these measures include multiple close-by forecast errors and can only be large when these forecast errors are systematically large and of opposite signs; even though this approach might come at the cost of including information from shocks that occurred in the period when the prices were set and before.

But we can do more: first, we redo our analysis regarding price increases and price

quarterly case. Finally, the results are also robust to estimating separate probit regressions for price increases and decreases. All of these results are available on request.

[28] Recall that we use t and τ to denote quarters and months, respectively. Therefore, $t + 1$ quarterly corresponds to $\tau + 3$ monthly.

decreases, now directly including current forecast errors and thus controlling for correlated first- and second-moment effects. Second, we change our assumption regarding what firms know when they set prices: instead of knowing the size of the forecast error tomorrow, the firms now only know the forecastable or systematic part of said forecast error. This is arguably the more reasonable information assumption, albeit not the one that maximizes the possibility of a pure "wait-and-see" effect. Put differently, firms are now not uncertain about the future because they happen to know that tomorrow, perhaps just once and thus unsystematically, a large shock occurs or because today they experienced a certain shock. Instead they are uncertain about tomorrow because, in line with a stochastic volatility view, they can form systematic expectations about the size of their forecast error tomorrow using the size of current and past forecast errors. Finally, we employ larger windows for our rolling window standard deviation measure, which will also mitigate the danger that we just pick up unsystematically large forecast errors, that is, pure wrongness, or a string of large, but systematically positive (negative) forecast errors, given that the standard deviation subtracts off their mean.[29]

Our analysis regarding price increases and decreases in the previous section provides a natural way to directly control for first-moment effects by including the realized forecast error of period t as an additional regressor. Specifically, we now assume that the decision of a firm to increase (or decrease) its price is a function of uncertainty, e.g., $ABSFE_t$, plus all of our standard controls and the realized forecast error, FE_t, in that period:[30]

$$\Delta p_t = f\left(ABSFE_t, FE_t, \ldots\right) \ . \tag{8}$$

Table 10 shows the results: including the forecast error does not change the finding that an increase in volatility increases the probability of a price change. We further find that the first-moment shocks affect the price setting decision of firms in an intuitive way. A positive (negative) forecast error causes a higher likelihood for a price increase (decrease). Interestingly, the importance of the forecast error diminishes when we include all firm-specific variables described in Table 6 (see columns with header (2) in Table 10), confirming that these controls indeed help absorb first-moment effects.

Next, we employ a two-stage approach to focus on the systematic part of the absolute

[29]In addition, in Appendix C.2, we use our firm-level forecast errors to compute cross-sectional dispersion measures, that is, another true second moment, for randomly selected subgroups at each point in time. Again we find a systematically positive relationship between these dispersion measures and the frequency of price adjustment within a subgroup.

[30]Recall that $ABSFE_t^{qual}$ and $ABSFE_t^{quan}$ (as well as the rolling window standard deviations) are defined by using next period's forecast error, i.e., we use the forecast in t and the realization in $t+1$ (see equation (1)).

Table 10: Robustness: forecast errors as controls

	Price increase		Price decrease	
	(1)	(2)	(1)	(2)
$ABSFE_t^{qual}$	0.001***	0.001**	0.002***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
FE_t^{qual}	0.006***	0.000	-0.006***	-0.000*
	(0.001)	(0.000)	(0.001)	(0.000)
Observations	242,554	194,253	242,554	194,253
$ABSFE_t^{quan}$	0.013	0.007	0.067***	0.051**
	(0.010)	(0.008)	(0.023)	(0.022)
FE_t^{quan}	0.043***	0.022*	-0.017	0.020
	(0.016)	(0.012)	(0.016)	(0.021)
Observations	30,588	27,106	30,588	27,106
$STDFE_t^{qual}$	0.005***	0.004***	0.009***	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)
FE_t^{qual}	0.009***	0.000	-0.008***	-0.000
	(0.001)	(0.001)	(0.001)	(0.000)
Observations	230,416	184,911	230,416	184,911
$STDFE_t^{quan}$	0.034	0.022	0.164**	0.201**
	(0.037)	(0.030)	(0.072)	(0.098)
FE_t^{quan}	0.082**	0.031	-0.058	-0.017
	(0.039)	(0.027)	(0.042)	(0.056)
Observations	16,828	14,987	16,828	14,987

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

Notes: Table presents marginal effects; robust and clustered (by firm) standard errors are in parentheses. Included in all multinomial logit models but not shown in the table are time-fixed effects for each quarter, industry-specific dummies, and Taylor dummies. Models (2) include, in addition, all firm-specific variables described in Table 6, except *Technical Capacity* and *Expected Employees* for the quantitative models. Quarterly price increases and decreases defined as described in Section 3.3.

forecast errors, which we can interpret as uncertainty/volatility as opposed to mere wrongness. To this end, in the first stage, we regress $ABSFE^{qual}$ and $ABSFE^{quan}$ on their respective lags. The upper panel of Table 11 shows that the lags have explanatory power for both the qualitative and the quantitative volatility proxy. The high values of the F-statistic support this finding. Both $ABSFE^{qual}$ and $ABSFE^{quan}$ are therefore systematically varying over time and are not just driven by large one-off first-moment shocks. We then estimate a second stage that is identical to our baseline model except for the fact that we use the fitted values from the first-stage regression (i.e., the systematic part of the forecast errors) as our volatility proxy. Standard errors in the second stage are bootstrapped using 100 repetitions. The results are shown in the lower panel of Table 11. Results are highly significant for $ABSFE^{qual}$ with point estimates that are slightly larger than in the baseline. For the quantitative volatility proxy $ABSFE^{quan}$, the estimates are quantitatively similar to the baseline, albeit statistically insignificant in some cases, possibly partly due to the loss in observations.

Table 11: Robustness: the systematic component of volatility

	First stage							
Dep. variable:	$ABSFE^{qual}$				$ABSFE^{quan}$			
$ABSFE_{t-1}$	0.173***	0.155***	0.146***	0.140***	0.444***	0.377***	0.337***	0.245***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.021)	(0.035)	(0.046)	(0.059)
$ABSFE_{t-2}$		0.112***	0.099***	0.090***		0.185***	0.136	0.133*
		(0.003)	(0.003)	(0.003)		(0.039)	(0.084)	(0.075)
$ABSFE_{t-3}$			0.090***	0.077***			0.169***	-0.027
			(0.003)	(0.003)			(0.049)	(0.039)
$ABSFE_{t-4}$				0.093***				0.307***
				(0.003)				(0.048)
F-statistic	3034.41***	2102.97***	1678.64***	1554.99***	435.46***	134.60***	128.07***	63.78***
	Second stage							
Dep. variable: price change								
Fitted values of $ABSFE$	0.045***	0.039***	0.032***	0.026***	0.138	0.207*	0.248	0.110
	(0.005)	(0.004)	(0.004)	(0.004)	(0.085)	(0.123)	(0.362)	(0.231)
Observations	245,515	228,884	214,491	201,734	29,661	16,181	10,047	6,789

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

Notes: Two-stage procedure: *first stage:* OLS-regression of uncertainty proxy on lags of uncertainty proxy. *Second stage:* probit model: price change on time-fixed effects, industry-specific dummies, Taylor dummies, and fitted values from the first-stage estimation. Models (represented in columns) vary in number of lags and in the uncertainty proxy used. The table presents marginal effects for the second stage. Robust and clustered (by firm) standard errors of the marginal effects (reported in parentheses) are computed using a bootstrap with 100 repetitions.

Recall that the rolling window standard deviation measure of volatility guards against the possibility of a string of large forecast errors of the same sign being interpreted as large uncertainty/volatility. It is also important to note that this case is not addressed by our first two robustness checks, which is why the rolling window standard deviation is important to be included as one of the baseline cases. In our baseline estimations, we keep the window short at three periods as missing values in our panel lead to a large reduction in the number of observations. In this robustness check, we allow for missing values, ensuring that we have at least three observations in each window, which allows us to increase the window size up to nine periods. The estimates, shown in Table 12, are very similar to those from the three-period window. The overall picture that the volatility effect dominates is robust.[31]

[31] Of course, using a symmetric window means that by increasing the window size, we look further and further into the future, making it more likely that price changes themselves affect the volatility measure. We therefore also consider purely backward looking windows. Table 22 in Appendix C.1 shows that this is not driving our results.

Table 12: Robustness: symmetric rolling windows of size 3, 5, 7, and 9

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable: price change								
Window size	$STDFE^{qual}$							
3	0.029***				0.013***			
	(0.002)				(0.002)			
5		0.028***				0.010***		
		(0.002)				(0.002)		
7			0.027***				0.010***	
			(0.002)				(0.002)	
9				0.028***				0.010***
				(0.002)				(0.002)
Observations	244,069	261,265	264,966	263,152	195,123	208,182	210,925	209,474
Window size	$STDFE^{quan}$							
3	0.188***				0.140**			
	(0.063)				(0.063)			
5		0.121***				0.067**		
		(0.036)				(0.030)		
7			0.093***				0.060***	
			(0.023)				(0.020)	
9				0.063***				0.038**
				(0.017)				(0.016)
Observations	16,956	46,880	72,437	93,369	15,095	41,329	63,584	81,720

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

Notes: Table presents marginal effects; robust and clustered (by firm) standard errors are in parentheses. Models (1) to (4) include time-fixed effects for each quarter, industry-specific dummies, and Taylor dummies. Models (5) to (8) include, in addition, all firm-specific variables described in Table 6, except *Technical Capacity* and *Expected Employees* for the quantitative models. Missing values allowed in the construction of $STDFE$ but at least three observations within a window are required.

4.2 Measurement

In this section, we deal with a number of potential measurement issues concerning both the price changes and our measures of business volatility. First, we change the timing of the volatility proxies towards the same period as when the price change occurs rather than from one period ahead. Recall that we made this rather strong baseline assumption to give the pure "wait-and-see" uncertainty effect its best chance. However, we have seen that even in this case, the volatility effect dominates, which is why we now study the case where only today's forecast error (in absolute value), that is, realized uncertainty today, is known today and can be used as a proxy for uncertainty about the future and future volatility, the arguably more realistic assumption. Second, with the help of price plan questions in the ifo survey, we redo our analysis only on unplanned price changes. Third, in light of the apparent unimportance of the role of pure uncertainty effects, we relax a number of assumptions made in the construction of the quantitative volatility proxies, thus moving them away from being based on true surprises to being based on changes. Fourth, and finally, we employ a control function approach to extract that component of the firms' forecast errors that the firms plausibly react to in their pricing decisions, which is arguably orthogonal to pure measurement error.[32]

Table 13: Robustness: alternative timing of volatility and unexpected price changes

Dependent variable: price change								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Volatility proxy at time of realization				
ABSFE^{qual}	0.017***				0.005***			
	(0.001)				(0.001)			
ABSFE^{quan}		0.099***				0.054***		
		(0.014)				(0.011)		
STDFE^{qual}			0.016***				0.006***	
			(0.002)				(0.001)	
STDFE^{quan}				0.063*				0.013
				(0.037)				(0.031)
Observations	270,305	67,958	246,580	17,091	214,941	59,677	197,193	15,250
				Unexpected price changes				
ABSFE^{qual}	0.008***				0.004***			
	(0.001)				(0.001)			
ABSFE^{quan}		0.068***				0.048***		
		(0.015)				(0.013)		
STDFE^{qual}			0.033***				0.017***	
			(0.003)				(0.002)	
STDFE^{quan}				0.238***				0.200***
				(0.079)				(0.081)
Observations	209,298	53,436	197,887	14,096	166,970	47,181	158,310	12,5775

*** 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: alternative timing where realized expectation error is contemporaneous with the pricing decision; second 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, industry-specific dummies, and Taylor dummies. Models (5) and (7) include, in addition, all firm-specific variables described in Table 6. 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; $STDFE^{qual}$: 3-quarter rolling window standard deviation of a firm's qualitative expectation errors; $STDFE^{quan}$: 3-quarter rolling window standard deviation of a firm's quantitative expectation errors.

The first robustness check (Table 13, upper panel) concerns the timing of the firm-specific volatility measures, especially for $ABSFE^{qual}$ and $ABSFE^{quan}$. In this robustness check, we change the timing structure so that the realized expectation error is contemporaneous with the pricing decision, and the results remain similar.

[32]We provide two additional robustness checks concerning the qualitative volatility proxies in Appendix C.1. First, as they are available at the monthly frequency, we redo our baseline estimations at this frequency with basically unchanged results (see Table 23, upper panel). We also 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 Table 23, lower panel).

The second robustness check (Table 13, 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).[33] Thus, in this exercise, we focus on price changes that are unexpected and check whether they react to idiosyncratic volatility. Again, the overall picture does not change.

For the construction of the quantitative volatility measures, we imposed a number of restrictions on our sample. For instance, we only included firms that had constant production expectations in order to capture production expectation errors. Since our baseline results show that the volatility effect dominates the "wait-and-see" effect of uncertainty empirically, we also check, as a plausibility check, whether we get the same results if we focus on production changes as opposed to production expectation errors. Table 14 (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 capacity utilization changes, the results still hold (see Table 14, middle panel). Finally, we conduct a similar exercise for the volatility measures based on qualitative production expectation errors (see Table 14, lower panel). To be specific, we use $REALIZ_{i,t+1}$ instead of $FE^{qual}_{i,t+1}$ in equation (1). Again our results remain essentially unchanged.

More generally, one might be concerned that measurement error contaminates our production forecast error measures. To deal with this problem directly and econometrically, we use the so-called control function approach (see Imbens and Wooldridge, 2007; Rivers and Vuong, 1988; Wooldridge, 2002), a two-stage instrumental variables procedure that can also be applied to nonlinear models and functions of endogenous variables, including absolute values. In the first stage, we regress each forecast error type, that is, $FE^{qual}_{i,t+1}$ and $FE^{quan}_{i,t+1}$, on the level of capacity utilization, the change of input costs, two dummies for the business situation, two dummies for the change of orders from period t (see Table 6),[34] plus Taylor and industry dummies, and time-fixed effects. Since firms by definition do not react to measurement error, the idea behind this first stage is to separate that component of the measured forecast error to which firms react with observable actions, and thus the

[33] To be concrete, we exclude price changes where firms stated a quarter before that they expect a price change and they followed through with the price change in the expected direction.

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

Table 14: Robustness: relaxing restrictions in construction of quant. forecast errors

Dependent variable: price change				
	(1)	(2)	(3)	(4)
Volatility based on production changes				
ABS^{quan}	0.120***		0.105***	
	(0.017)		(0.020)	
STD^{quan}		0.120***		0.081**
		(0.039)		(0.040)
Observations	80,884	23,545	70,375	20,485
Volatility based on capacity utilization changes				
ABS^{quan}	0.136***		0.099***	
	(0.011)		(0.012)	
STD^{quan}		0.176***		0.115***
		(0.016)		(0.015)
Observations	194,298	129,695	168,063	111,441
Qualitative production change				
ABS^{qual}	0.031***		0.016***	
	(0.001)		(0.001)	
STD^{qual}		0.035***		0.015***
		(0.002)		(0.002)
Observations	263,469	244,517	209,697	195,424

*** 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: 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., $REALIZ_{i,t+1}$ replaces $FE^{qual}_{i,t+1}$ in equation (1). Included in all models but not shown in the table are time-fixed effects for each quarter, industry-specific dummies, and Taylor dummies. Models (3) and (4) include, in addition, all firm-specific variables described in Table 6, except *Technical Capacity* and *Expected Employees* in the specification of the first panel.

true forecast error, from measurement error. In the second stage, we estimate our baseline probit model which includes our volatility measures on the right hand side (plus Taylor and industry 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 potential endogeneity in our volatility measures. The results are essentially unchanged (see Table 15).[35] Also, the second-stage coefficient of the first-stage residual is statistically not distinguishable from zero, which means that measurement error does not appear to drive our results.

[35]We only study the absolute value version of our business volatility proxies here, because the rolling window standard deviation measures contain forecast errors from multiple periods and are thus difficult to handle in a control function approach.

Table 15: Robustness: control function approach

Dependent variable: price change		
	(1)	(2)
$ABSFE^{qual}$	0.014***	
	(0.002)	
$ABSFE^{quan}$		0.118***
		(0.023)
Observations	204,117	56,624

*** 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. Second stage includes time-fixed effects, industry dummies, Taylor dummies, and the residual of the first stage. Included in the probit model but not shown in the table are time-fixed effects, industry-specific dummies, and Taylor dummies.

4.3 Financial constraints

Gilchrist et al. (2017) argue that financial frictions are an important determinant of firms' price setting decisions. To the extent that financing constraints are related to uncertainty, we might link price changes to variations in uncertainty that were in reality due to changes in financial conditions. In our final robustness check, we therefore follow Balleer et al. (2017) and make use of a question regarding the financial constraints of firms, which was introduced into the ifo survey in 2003. It is a special question that was added as a result of the acute difficulties of the German banking system at that time. Specifically, firms are asked about their access to bank lending: "How do you evaluate the current willingness of banks to grant credits to businesses? Restrictive, normal, or accommodating?" (see Table 1).

We re-estimate our baseline model on the sample starting in 2003, and then estimate it with the additional credit constraint variable.[36] There are two things to note: first, the results without the credit constraint variable are very similar to those estimated on the baseline sample starting in 1980. Second, results are not affected by controlling for financing constraints of the firms.

[36] As with the firm-specific variables in the baseline specification in Section 3.2, we allow for potential asymmetric effects by including $Credit^{+}_{i,t}$ and $Credit^{-}_{i,t}$ separately.

Table 16: Robustness: model with and without credit question

Dependent variable: price change								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$ABSFE^{qual}$	0.006***	0.005***						
	(0.002)	(0.002)						
$ABSFE^{quan}$			0.093***	0.083**				
			(0.035)	(0.033)				
$STDFE^{qual}$					0.015***	0.014***		
					(0.004)	(0.004)		
$STDFE^{quan}$							0.323	0.299
							(0.220)	(0.203)
$credit^{+}$		0.024***		0.036***		0.020***		0.030
		(0.007)		(0.013)		(0.007)		(0.032)
$credit^{-}$		0.017***		0.025**		0.016***		0.058**
		(0.005)		(0.010)		(0.005)		(0.026)
Observations	31,202	31,202	7,887	7,887	27,806	27,806	1,760	1,760

*** 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 probit model but not shown in the table are time-fixed effects for each quarter, industry-specific dummies, Taylor dummies, and the firm-specific variables described in Table 6. The sample period is from 2003 to 2015.

5 Quantitative price change measures and volatility

Our analysis so far has shown that there is a positive relationship between firm-level volatility and the frequency of price adjustment (extensive margin). However, the qualitative price data in the ifo dataset does not allow us to analyze whether uncertain firms change their prices by smaller or larger amounts than less uncertain firms (intensive margin). Yet, the behavior of the intensive margin has also implications for the modeling of inflation dynamics. E.g., for U.S. CPI micro data, Vavra (2014) stresses the fact that the price adjustment frequency and the price change dispersion are positively correlated. Furthermore, the price change dispersion is countercyclical in U.S. data.[37] These findings can be replicated by a standard menu cost model only by incorporating countercyclical second-moment shocks.

To get a sense of how firms adjust their intensive price setting margin to firm-level volatility, we use the micro data underlying the German producer price index provided by the German Federal Statistical Office (PPI henceforth). Unfortunately, we cannot match this dataset to the ifo data, so we have no measures for firm-specific volatility in the PPI data and, therefore, cannot estimate firm-level regressions. Our analysis will hence be based on (Choleski-identified) structural vector autoregressions (SVARs).

[37] Table 17 below confirms that also in German PPI data the price change dispersion rises in recessions. Moreover, the unconditional correlation between the price change dispersion and the price adjustment frequency is 0.15 for the German PPI data, and 0.41 when ifo price frequency adjustment data are used. Finally, the IRF in Figure 2 below shows that this positive correlation between the extensive and the intensive margins of price adjustment also and a fortiori holds conditional on a volatility shock.

5.1 Micro data of the German producer price index

As mentioned above, in this section, we use micro data underlying the German producer price index, available from 2005q1 to 2015q4.[38] Note that these micro data do not include price changes due to sales and that the Federal Statistical Office controls for product improvements.

To make our analysis comparable to that based on the ifo data, we compute quarterly growth rates from quarterly averages of the price levels.[39] We define a price change to have occurred if the quarterly growth rate is unequal to zero. In the beginning of the sample, we have roughly 6,400 observations, which increases to slightly more than 8,500 observations at the end of the sample.[40]

Table 17: PPI and ifo price data: descriptive statistics

	Data Source	Mean	Mean Recession 2008/09	Standard Deviation	Correlation with ifo counterpart
Price change frequencies (in percent)					
Price changes	ifo	32.80	38.37	5.01	
	PPI	44.58	48.39	5.11	0.77
Price increases	ifo	19.02	19.62	7.67	
	PPI	27.56	29.66	6.85	0.81
Price decreases	ifo	12.82	18.03	5.67	
	PPI	17.00	19.05	3.43	0.79
Size and volatility of price changes (in percent)					
Mean absolute value	PPI	3.51	4.85	0.92	
Dispersion	PPI	4.92	6.84	1.42	
Interquartile range	PPI	4.32	5.68	1.07	

Notes: To compute the statistics we use quarterly data from 2005q1 to 2015q4. All data are seasonally adjusted. Size and volatility of price changes are computed based on price changes unequal to zero. For the cross-sectional mean absolute value, the cross-sectional standard deviation (dispersion), and the cross-sectional interquartile range, we clean our data from outliers by removing quarterly observations that are smaller than the 1st percentile and larger than the 99th percentile of the corresponding quarter. To compute these percentiles, we use all observations including no price changes.

[38]Before 2005 the price data were collected regionally by the statistical offices of the individual federal states (Länder) and are not available to us.

[39]The underlying data is available at the monthly level.

[40]We clean our data from outliers by removing quarterly observations that are smaller than the 1st percentile or larger than the 99th percentile of the corresponding quarter. To compute these percentiles we use all observations including no price changes. All series are seasonally adjusted.

We start by providing some descriptive statistics and a comparison to the ifo data. The first entry in the upper panel of Table 17 is the proportion of price changes in a given quarter. With a correlation coefficient of 0.77, the series from both sources are highly correlated; even more so when looking at price increases and decreases separately, corroborating that the ifo data are of high quality.

The upper panel of Table 17 further shows the average price adjustment frequencies for the recession of 2008/09. Similar to the numbers earlier reported for the ifo data in Table 5, we see again that the Great Recession raised the average price adjustment frequency by a significant amount in both ifo and PPI data.

The lower panel of Table 17 presents the additional statistics that we can only compute for the quantitative PPI data. The statistics are computed conditional on observing a price change (including small price changes but cleaned for outliers). Our calculations show that when a firm decides to adjust its price, it does so by roughly 3.5 percent on average. This number was 1.3 percentage points larger in the recession of 2008/09. The cross-sectional standard deviation (dispersion) of price changes is slightly less than 5 percent on average. This number increased by 1.9 percentage points in the last recession.

The key takeaway from this section is that the extensive and intensive margins of price changes and their dispersion are countercyclical.

5.2 The dynamic effects of firm-level volatility on prices

We now use an SVAR model to analyze the aggregate effects of increases in firm-level volatility (from the ifo data) on quantitative pricing moments (from the quantitative PPI data). While the PPI data only start in 2005q1 and end in 2015q4, this time span nonetheless covers the recession of 2008/09, the Euro crisis in 2011/12, and the booms in the periods 2007/08 and 2010/11.

Our VAR setup is an extended version of that used by Bachmann et al. (2013). Formally, we estimate the following model:

$$y_t = \mu + A(L)y_{t-1} + \nu_t \ , \tag{9}$$

where μ is a constant, $A(L)$ is a lag polynomial of degree $p = 4$, and $\nu_t \overset{iid}{\sim} (0, \Sigma)$. The vector of endogenous variables y_t comprises five variables at the quarterly frequency, approximating the information set of our baseline micro data investigation. Specifically, y_t contains (in the listed order) the balance of firms' production expectations determined by the ifo data, one of our volatility measures, the log of West-German manufacturing production, the log of the

HWWI price index for energy raw materials (in Euro),[41] and a quantitative pricing moment (cleaned of outliers). All variables are seasonally adjusted. The choice of variables ensures that we control for forward-looking information as well as cost developments.

As a baseline, we start with the two quantitative volatility proxies: the quarterly average absolute ex-ante errors, $\overline{ABSFE}_t^{quan}$ and the average asymmetric (i.e., backward looking) 3-quarter rolling window standard deviation based on ex-ante forecast errors, $\overline{STDFE}_t^{quan}$.[42] Pricing moments considered in this first set of estimates are the price change frequency for both ifo and PPI data and the mean price change, the mean absolute price change, and the dispersion of price changes from the PPI dataset excluding zero changes.

To identify the volatility shock, we assume a recursive identification scheme with a standard ordering of variables (see, e.g., Bloom, 2009; Jurado et al., 2015). Specifically, we impose the restriction that volatility reacts contemporaneously to exogenous changes in production expectations but not to variations in manufacturing production. We further assume that volatility has an immediate impact on manufacturing production. For the quantitative pricing moment, we assume that it can react contemporaneously to the volatility shock.

Figure 2 shows impulse response functions (IRFs) to one-standard-deviation volatility shocks and the corresponding bootstrapped 68% and 95% confidence intervals. Each column represents one of the quantitative volatility proxies, and each row represents one of the quantitative pricing moments. That is, each panel represents a different SVAR.[43] For the frequency of price changes (first row), we also include the estimated response of the ifo series.

The first row of Figure 2 shows that a surprise increase in business volatility leads to an increase in the price change frequency, corroborating the findings from our firm-level analysis. We also find that higher volatility has a negative impact on the price level (second row).[44] This is consistent with the evidence in Born and Pfeifer (2017) who find that, empirically, price markups and inflation tend to fall after uncertainty shocks.

Next, volatility shocks cause protracted increases in price dispersion and in the mean of the absolute price changes (rows 3 and 4) which fits the evidence in Vavra (2014). In the case of $\overline{ABSFE}_t^{quan}$, we find that a one-standard-deviation business volatility shock leads to a rise in price dispersion (mean of the absolute price changes) by 0.5 percentage points (0.3 percentage points) after one quarter.

[41]This series is constructed and published by the Hamburg Institute of International Economics (HWWI).

[42]Similar results for the qualitative measures are shown in Figures 5 and 6 in Appendix D.

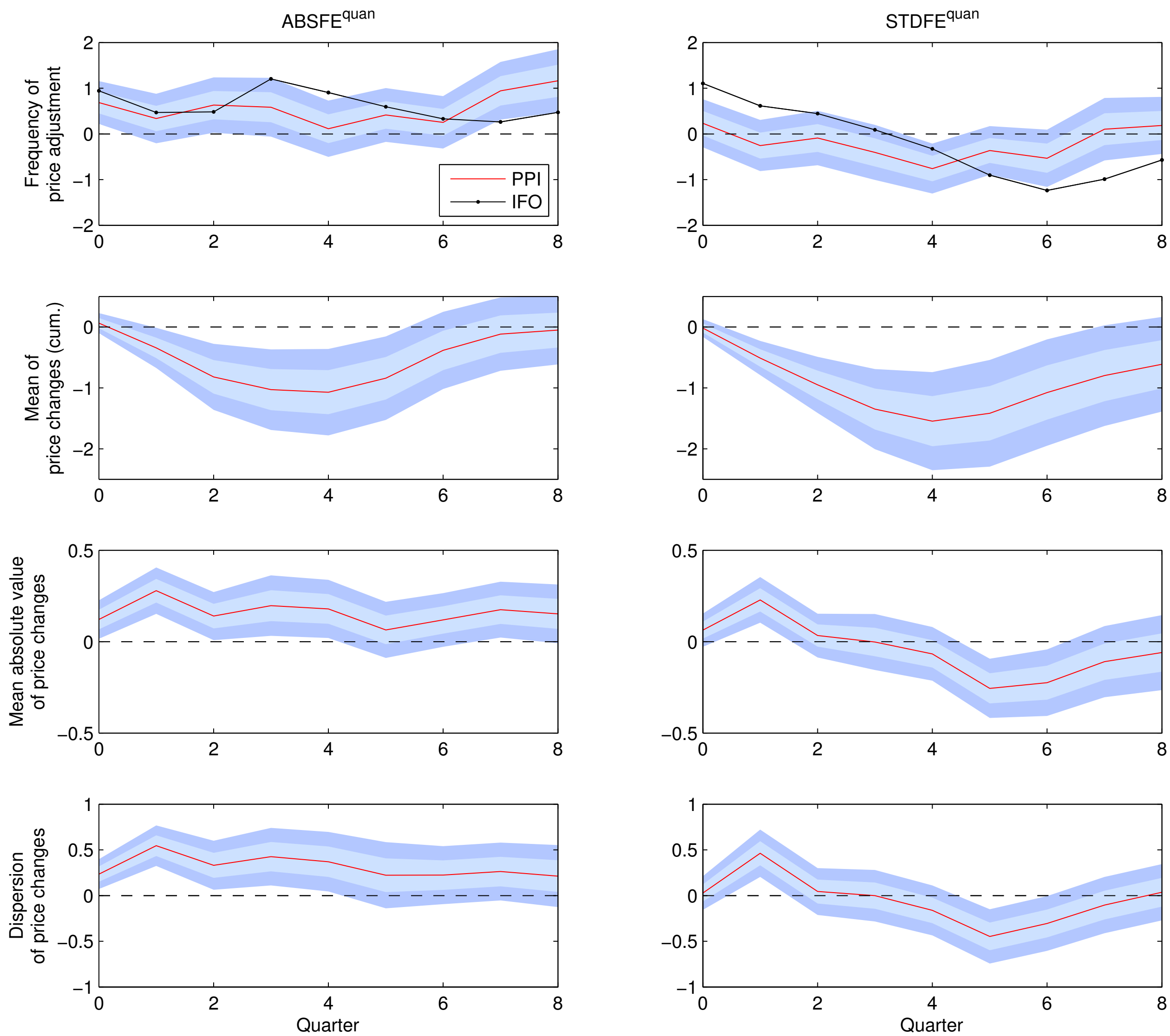
[43]The IRFs of the other variables look similar to those found in the literature and are available on request.

[44]Note that we plot the cumulated mean price change response. This is not quite equal to the development of the total level PPI as we only consider price changes excluding zeros.

In summary, this first set of SVAR estimates delivers three findings: first, we again find evidence that the price change frequency reacts positively, certainly not negatively, as would be implied by the dominance of "wait-and-see" effects, to uncertainty/volatility increases. Second, volatility appears to have a negative impact on the price level. Third, increases in volatility lead to more dispersed price changes.

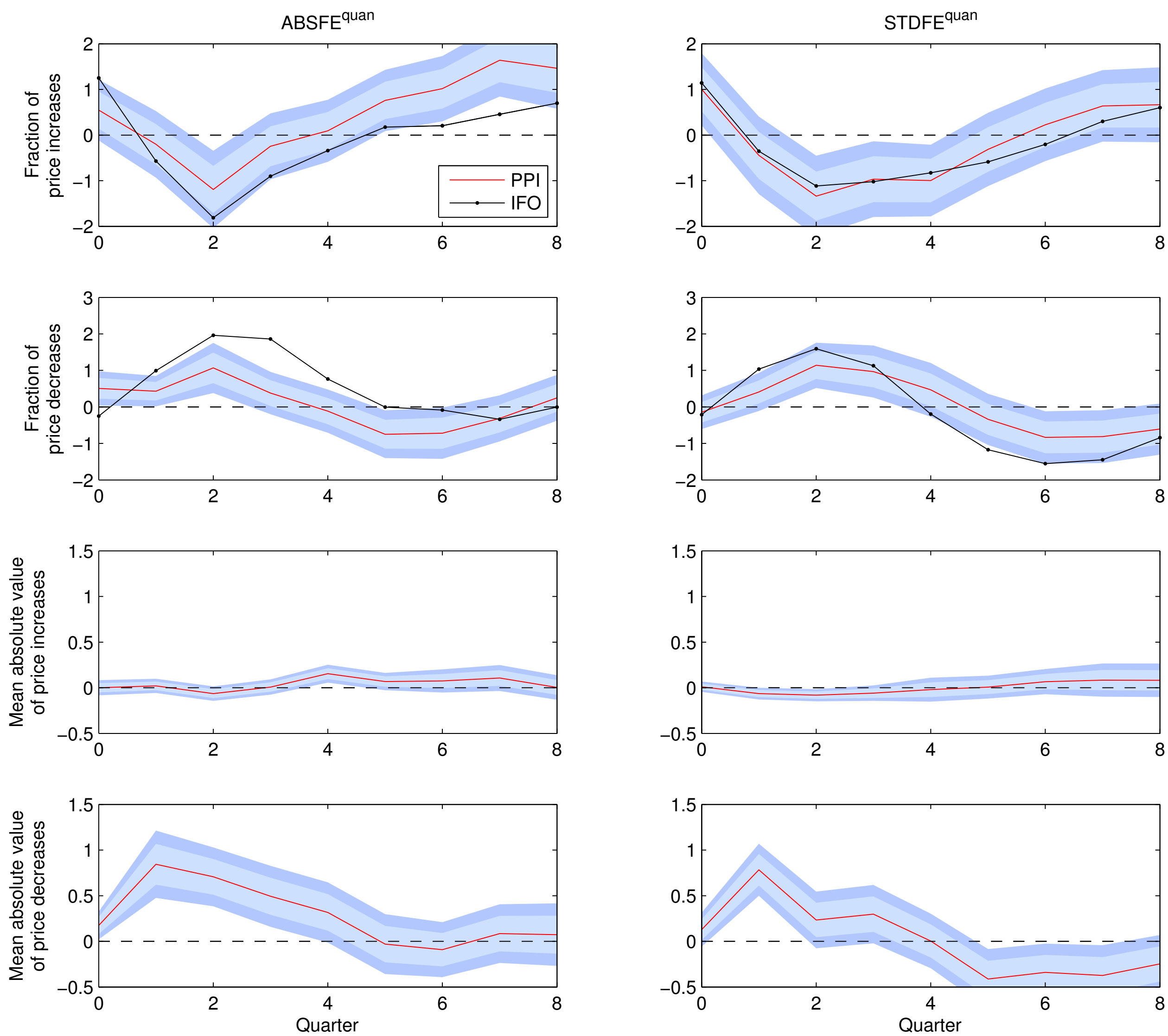
To shed further light on the transmission of business volatility shocks to prices, we next distinguish between price increases and price decreases. The first row of Figure 3 shows that the fraction of price increases rises significantly for $\overline{ABSFE}_t^{quan}$ and $\overline{STDFE}_t^{quan}$. After two quarters, however, the response turns negative, and only recovers/turns positive again after about a year. In contrast to this, we find a delayed positive response of the fraction of price decreases. While we see almost no reaction in the mean absolute value for price increases, the positive reaction for price decreases is significantly larger. This means that the increase in total price dispersion after a business volatility shock is largely driven by the dynamics of price decreases. Conversely, conditional on an upward price adjustment after an increase in business volatility, it is mainly the extensive margin that operates, perhaps suggesting that firms follow a routine pricing rule conditional on upward adjustment. Conditional on downward price adjustment after an increase in business volatility, we see, by contrast, both the extensive and the intensive margins of price adjustment active, perhaps a sign that this constitutes an unusual moment for the firm that requires some experimentation with prices.

Figure 2: IRFs to business volatility shocks: price change moments



Notes: IRFs based on model (9). Left and right columns: responses of pricing moments to innovations in $\overline{ABSFE}_t^{quan}$ and $\overline{STDFE}_t^{quan}$, respectively. All responses are percentage point deviations. For the mean of price changes we display the cumulated response. The mean of price changes, the mean of absolute price changes, and the dispersion of price changes are based on price changes excluding zero changes. Shaded regions are 68% and 95% bootstrapped confidence intervals. Sample period for estimation is 2005q1 - 2015q4.

Figure 3: IRFs to business volatility shocks: price increases and decreases



Notes: IRFs based on model (9). Left and columns: responses of pricing moments to innovations in $\overline{ABSFE}_t^{quan}$ and $\overline{STDFE}_t^{quan}$, respectively. All responses are percentage point deviations. The mean of absolute price changes is based on price changes excluding zero changes. Shaded regions are 68% and 95% bootstrapped confidence intervals. Sample period for estimation is 2005q1 - 2015q4.

6 Conclusion

The contribution of this paper is twofold. Using micro data from West German manufacturing firms provided by the ifo Business Climate Survey, we construct measures of firm-level uncertainty/volatility. Specifically, we compute firm-specific expectation errors and use their absolute values and rolling window standard deviations as measures of idiosyncratic business volatility. We then find that the frequency of price adjustment increases in idiosyncratic business volatility and thus confirm theoretical predictions from various literatures about the sign of the relationship between uncertainty/volatility and the frequency of price changes.

In particular this means that, at least for price setting, the volatility effect of uncertainty dominates the "wait-and-see" effect. Overall, however, it seems that only a relatively small fraction of the time-series movements of the extensive margin of price adjustment can be explained by movements in idiosyncratic business volatility.

Second, we provide evidence that heightened firm-level volatility also leads to larger price adjustments (intensive margin) and to an increase in price dispersion, where the adjustment along the intensive margin is mainly driven by firms that decrease their prices.

More generally, it thus seems important to understand better why the extensive and intensive margins of pricing, and hence price rigidities, change so significantly over the business cycle and which consequences for monetary policy these fluctuations in both margins of price setting might have.

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A Correlations of disaggregated volatility measures

Table 18: Correlation coefficients between $\overline{STDFE}_{\tau}^{qual}$, $\overline{ABSFE}_{\tau}^{qual}$, and $FEDISP_{\tau}^{qual}$

Group of Firms	Correlation between $\overline{ABSFE}_{\tau}^{qual}$ and $FEDISP_{t}^{qual}$ raw data	seasonally adjusted	Correlation between $\overline{ABSFE}_{\tau}^{qual}$ and $\overline{STDFE}_{\tau}^{qual}$ raw data	seasonally adjusted
Manufacturing	0.93	0.92	0.87	0.86
Industry				
Transport equipment	0.91	0.90	0.63	0.68
Machinery and equipment	0.94	0.94	0.79	0.80
Metal products	0.92	0.92	0.77	0.78
Other non-metallic products	0.90	0.91	0.64	0.68
Rubber and plastic	0.86	0.85	0.55	0.62
Chemical products	0.89	0.89	0.56	0.56
Elect. and opt. equipment	0.94	0.94	0.74	0.75
Paper and publishing	0.90	0.90	0.76	0.80
Furniture and jewelery	0.88	0.87	0.39	0.44
Cork and wood products	0.93	0.93	0.65	0.71
Leather	0.92	0.92	0.48	0.55
Textile products	0.92	0.92	0.65	0.66
Food and tobacco	0.92	0.92	0.72	0.76
Firm Size				
less than 50 employees	0.92	0.93	0.77	0.80
between 50 and 199 employees	0.93	0.93	0.83	0.84
between 200 and 499 employees	0.94	0.94	0.77	0.79
between 500 and 999 employees	0.95	0.94	0.80	0.81
more than 999	0.95	0.94	0.76	0.79

Notes: Table provides in the first two columns time-series correlation coefficients between $\overline{ABSFE}_{\tau}^{qual}$ and $FEDISP_{t}^{qual}$ 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 $\overline{ABSFE}_{\tau}^{qual}$ and $\overline{STDFE}_{\tau}^{qual}$. 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 $\overline{ABSFE}_{\tau}^{qual}$, $FEDISP_{t}^{qual}$, and $\overline{STDFE}_{\tau}^{qual}$ is explained in Section 2.

B Description of the input cost variable

To compute a proxy for the cost of input goods, $Costs_{k,t}$ in industry k, we follow the approach outlined in Schenkelberg (2013). In this approach, a weighted price variable of all K industries that provide input goods for each production industry k is computed. This procedure follows three steps. First, we compute the weights of inputs for each industry k. To this end, we use data from input-output tables from the German Federal Statistical Office. These data provide for each industry k the cost of input goods from each industry l (including from its own industry). Data is available for the years 1991 to 2013. For each year we calculate the cost share of industry l that is used in the production process of industry k. Finally, we average these shares across time. Second, from the ifo survey we know whether a firm i from industry l changes its price in period t. We compute the net balance of price changes within a given industry l for each period t. That is, we subtract the fraction of price decreases from the fraction of price increases. We, therefore, need to assume that price increases (decreases) are similar across different firms within an industry. This gives us a proxy of the price of input goods from industry l. Third, we combine the weights of input goods from industry l in the production in industry k (from step one) with the respective price of goods from industry l at period t (from step two). The resulting time series is a proxy for input costs which industry 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 industries. The problem with this in principle superior measure is that the data are only consistently available since 1995. We proceed as above. We compute the quarterly inflation rates of the producer prices for each industry k. We combine the weights of input goods form industry l in the production process in industry k with the respective producer prices inflation rate from industry l. We get a time series of input costs for each industry 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 19. In almost all industries we find high correlations which lends credence to the use of $\text{Costs}_{k,t}$ since producer prices at the industry level are not fully available before 1995.

Table 19: Time-series correlation coefficients of input costs for each industry

Industry	Correlation between $\text{Costs}_{k,t}$ and $\text{Costs}^{ppi}_{k,t}$
Transport equipment	0.75
Machinery and equipment	0.66
Metal products	0.68
Other non-metallic products	0.74
Rubber and plastic	0.66
Chemical products	0.48
Elect. and opt. equipment	0.30
Paper and publishing	0.38
Furniture and jewelry	0.84
Cork and wood products	0.84
Leather	0.58
Textile products	0.72
Food and tobacco	0.53

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

C Additional robustness checks

C.1 Robustness tables

Table 20: Robustness: linear models

Dependent variable: price changes								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Linear (pooled) regression model				
$\text{ABSFE}^{\text{qual}}$	0.012***				0.006***			
	(0.001)				(0.001)			
$\text{ABSFE}^{\text{quan}}$		0.102***				0.082***		
		(0.018)				(0.020)		
$\text{STDFE}^{\text{qual}}$			0.034***				0.017***	
			(0.002)				(0.002)	
$\text{STDFE}^{\text{quan}}$				0.204***				0.161**
				(0.066)				(0.070)
Observations	263,224	66,330	244,069	16,956	209,562	58,353	195,123	15,095
				Linear panel fixed-effects model				
$\text{ABSFE}^{\text{qual}}$	0.005***				0.003**			
	(0.001)				(0.001)			
$\text{ABSFE}^{\text{quan}}$		0.049**				0.041*		
		(0.020)				(0.022)		
$\text{STDFE}^{\text{qual}}$			0.024***				0.013***	
			(0.002)				(0.002)	
$\text{STDFE}^{\text{quan}}$				0.201**				0.186*
				(0.094)				(0.110)
Observations	263,224	66,330	244,069	16,956	209,562	58,353	195,123	15,095

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

Notes: The table presents coefficients. Robust and clustered (by firm) standard errors are in parentheses. First panel: linear pooled OLS model; second panel: linear panel fixed-effects model. Included in all models but not shown in the table are time-fixed effects for each quarter, industry-specific dummies, and Taylor dummies. Models (5) to (8) include, in addition, all firm-specific variables described in Table 6, except *Technical Capacity* and *Expected Employees* for the quantitative models. $ABSFE^{qual}$: qualitative idiosyncratic volatility; $ABSFE^{quan}$: quantitative idiosyncratic volatility; $STDFE^{qual}$: 3-quarter rolling window standard deviation of a firm's qualitative expectation errors; $STDFE^{quan}$: 3-quarter rolling window standard deviation of a firm's quantitative expectation errors.

Table 21: Robustness: sample-split into non-recession and recession samples

Dependent variable: price change								
	Non-recession				Recession			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
$\text{ABSFE}^{\text{qual}}$	0.008***		0.004***		0.011***		0.007***	
	(0.001)		(0.001)		(0.002)		(0.003)	
$\text{ABSFE}^{\text{quan}}$		0.070***		0.055***		0.088***		0.069*
		(0.016)		(0.015)		(0.031)		(0.039)
Observations	175,945	47,081	141,770	41,760	87,279	19,249	67,792	16,593
$\text{STDFE}^{\text{qual}}$	0.027***		0.012***		0.041***		0.020***	
	(0.002)		(0.002)		(0.004)		(0.004)	
$\text{STDFE}^{\text{quan}}$		0.217***		0.161**		0.195		0.164
		(0.077)		(0.079)		(0.126)		(0.125)
Observations	164,222	12,495	132,795	11,145	79,847	4,461	62,328	3,950

*** 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 probit model but not shown in the table are time-fixed effects for each quarter, industry-specific dummies, and Taylor dummies. Models (3)-(4) include, in addition, all firm-specific variables described in Table 6, except *Technical Capacity* and *Expected Employees* for the quantitative models; $ABSFE^{qual}$: qualitative idiosyncratic volatility; $ABSFE^{quan}$: quantitative idiosyncratic volatility; $STDFE^{qual}$: 3-quarter rolling window standard deviation of a firm's qualitative expectation errors; $STDFE^{quan}$: 3-quarter rolling window standard deviation of a firm's quantitative expectation errors. Recessions dated by the German Council of Economic Experts (GCEE): 1980q1-1982q4, 1991q1-1993q3, 2001q1-2005q2, and 2008q1-2009q2.

Table 22: Robustness: asymmetric rolling windows of size 3, 5, 7, and 9

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable: price change								
Window size	$STDFE^{qual}$							
3	0.021***				0.008***			
	(0.002)				(0.001)			
5		0.020***				0.005***		
		(0.002)				(0.001)		
7			0.024***				0.007***	
			(0.002)				(0.002)	
9				0.028***				0.009***
				(0.002)				(0.002)
Observations	246,580	261,729	259,591	254,990	197,193	208,735	207,183	203,880
Window size	$STDFE^{quan}$							
3	0.068*				0.012			
	(0.039)				(0.036)			
5		0.077***				0.035		
		(0.026)				(0.024)		
7			0.074***				0.016	
			(0.023)				(0.018)	
9				0.052***				0.014
				(0.014)				(0.013)
Observations	17,091	46,666	71,492	91,155	15,250	41,201	62,920	79,948

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

Notes: Table presents marginal effects. Robust and clustered (by firm) standard errors are in parentheses. Models (1) to (4) include time-fixed effects for each quarter, industry-specific dummies, and Taylor dummies. Models (5) to (8) include, in addition, all firm-specific variables described in Table 6, except *Technical Capacity* and *Expected Employees* for the quantitative models. Missing values allowed in the construction of $STDFE$ but at least three observations within a window are required.

Table 23: Robustness: additional qualitative models

Dependent variable: price change				
	(1)	(2)	(3)	(4)
(a) Monthly model				
$ABSFE^{qual}$	0.004***		0.002***	
	(0.001)		(0.001)	
$STDFE^{qual}$		0.008***		0.003***
		(0.001)		(0.000)
(b) Volatility measure as dummy variable				
$ABSFE^{qual}$	0.020***		0.011***	
	(0.002)		(0.003)	

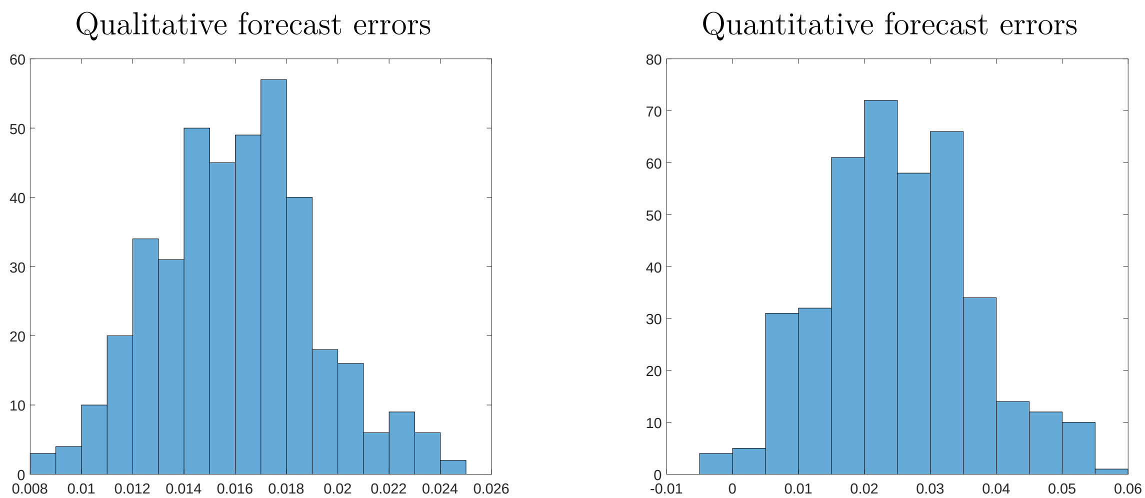
*** p<0.01, ** p<0.05, * p<0.1

Notes: The table presents marginal effects. All estimations are based on the probit model. First panel: volatility measure computed from monthly three-month-ahead qualitative production forecast errors; second 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 probit model but not shown in the table are time-fixed effects, industry-specific dummies, and Taylor dummies.

C.2 Regressions with a cross-sectional dispersion measure

In this robustness check, we use an alternative empirical approach to analyze the link between volatility and the price setting behavior of firms. The idea is to use the cross-sectional dispersion of forecast errors (see equation (6)) within a randomly drawn group of firms to construct a group-level volatility proxy. For the same random group of firms, we can also compute the share of price changes, so that we obtain a panel of firm groups for each of which we have a dispersion-based volatility proxy and a price change frequency measure.

Figure 4: Robustness: the cross-sectional dispersion of forecast errors



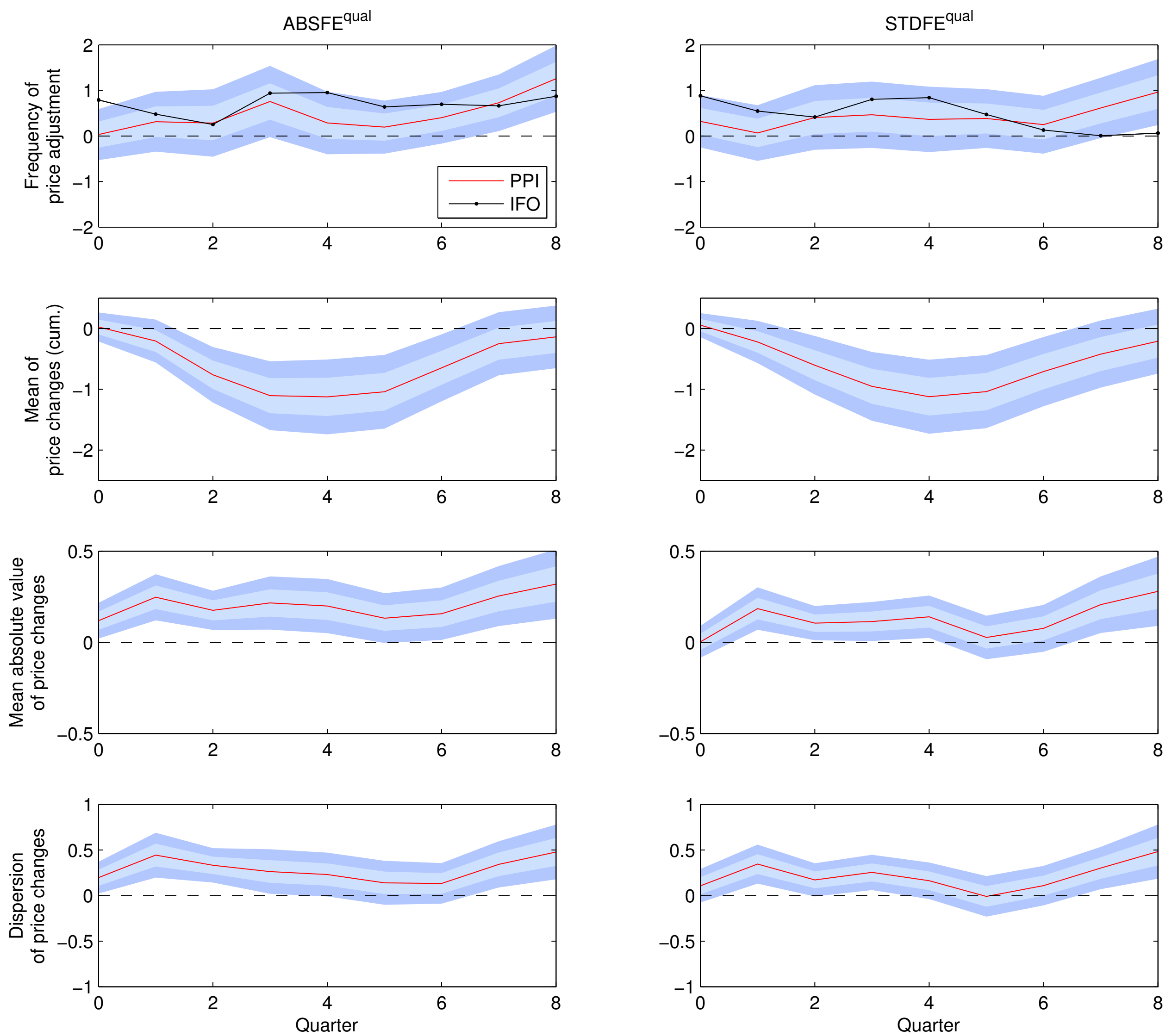
Notes: For each t, 150 groups of firms are randomly drawn. For each group, we compute the cross-sectional mean of price changes and the cross-sectional dispersion of the (qualitative and quantitative) forecast errors one period later. We regress the price change frequency on the cross-sectional dispersion of forecast errors (and on a set of time-fixed effects). This exercise is repeated 400 times. The histograms plot the frequency of estimated coefficient values.

Specifically, we first draw for each point in time in our sample 150 artificial groups that consist of 13 firms on average.[45] For each of these groups, we compute the within-group dispersion of forecast errors and the within-group share of firms that adjusted their price. We then regress the price adjustment measure on the volatility proxy (timed at the time of the forecast, as in the baseline) and a set of time-fixed effects. Repeating this 400 times gives us the distribution of estimated relationships between volatility and price setting shown in Figure 4. The mean estimate for the qualitative forecast error is 0.016 with a standard error across simulations of 0.003, for the quantitative forecast error the respective numbers are 0.025 and 0.011. Again we find a robustly positive relationship between business volatility and price setting.

[45]This number is just governed by the number of available firms. The results are robust to drawing 100 or 200 groups instead.

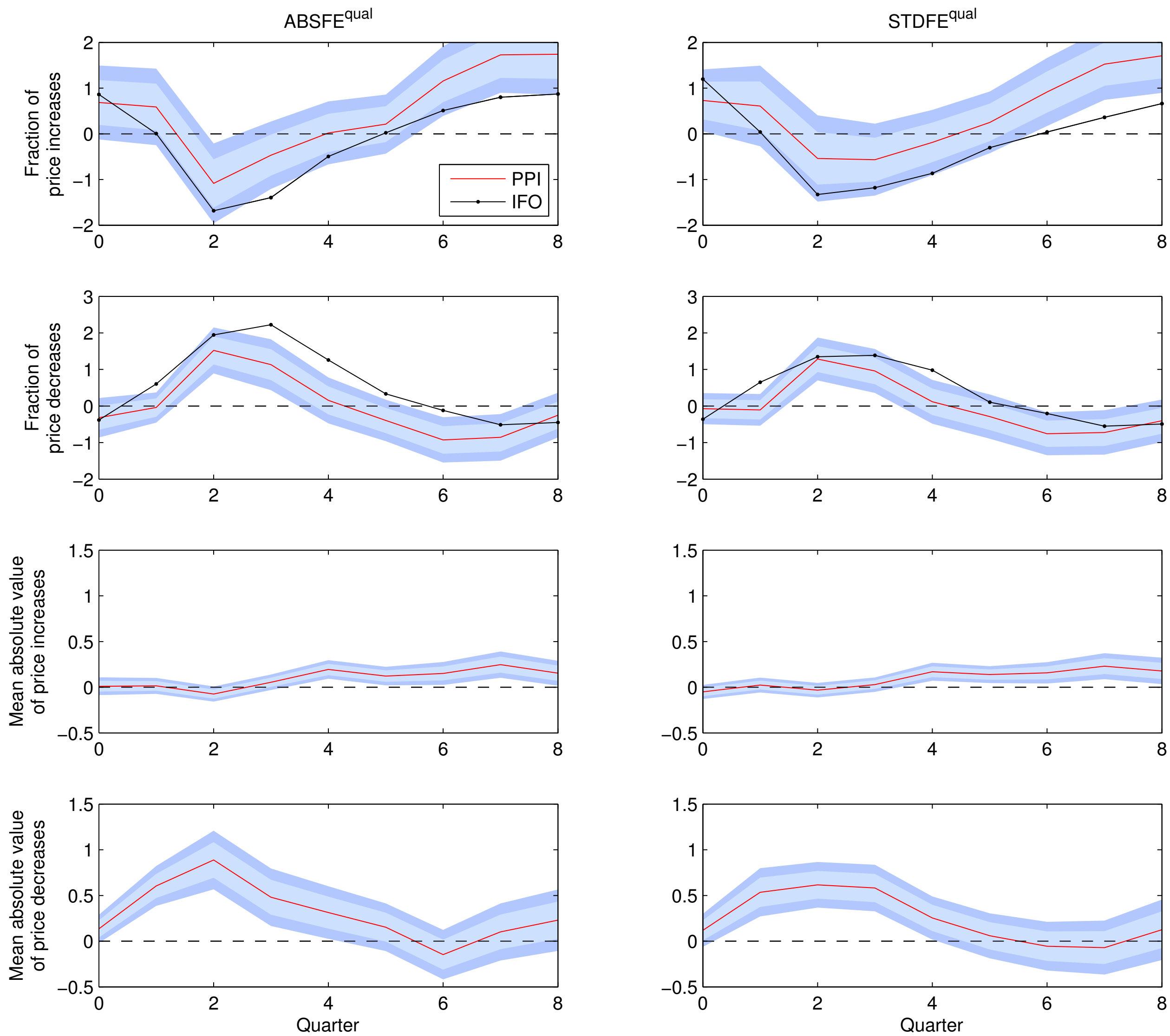
D SVARs with qualitative business volatility proxies

Figure 5: IRFs to business volatility shocks: price change moments



Notes: IRFs based on model (9). Left and right columns: responses of pricing moments to innovations in $\overline{ABSFE}_t^{qual}$ and $\overline{STDFE}_t^{qual}$, respectively. All responses are percentage point deviations. For the mean of price changes we display the cumulated response. The mean of price changes, the mean of absolute price changes and the dispersion of price changes are based on price changes excluding zero changes. Shaded regions are 68% and 95% bootstrapped confidence intervals. Sample period for estimation is 2005q1 - 2015q4.

Figure 6: IRFs to business volatility shocks: price increases and decreases



Notes: IRFs based on model (9). Left and right columns: responses of pricing moments to innovations in $\overline{ABSFE}_t^{qual}$ and $\overline{STDFE}_t^{qual}$, respectively. All responses are percentage point deviations. The mean of absolute price changes is based on price changes excluding zero changes. Shaded regions are 68% and 95% bootstrapped confidence intervals. Sample period for estimation is 2005q1 - 2015q4.