Uncertainty, Price Setting, and the Real Effects of Monetary Policy*

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Abstract

Does time-varying business uncertainty affect the price setting of firms and thus the real effects of monetary policy? To address this question, we first estimate a logit model to examine the role of idiosyncratic uncertainty on the price-setting behavior of German firms. Uncertainty measures are constructed from the German IFO Business Climate Survey. In a second step, we use a stylized New Keynesian business cycle model to gauge the effects of uncertainty on the transmission of monetary policy to output. Our results are threefold. First, idiosyncratic uncertainty can be well approximated by the absolute value of firm-specific expectation errors. Second, heightened uncertainty increases the probability of a price change, though the effect is small: the tripling of uncertainty during the recession of 08/09 caused the average quarterly likelihood of a price change to increase from 31.6% to 32.1%. Third, the effects of this increase in uncertainty on monetary policy are rather small; the initial effect of a 25 basis point monetary policy shock to output declines from 0.347% to 0.342%.

JEL-Classification: E30, E31, E32, E50
Keywords: Time-varying Uncertainty, Monetary Policy, Survey Data, Price Setting, New Keynesian Model

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1 Introduction

Does time-varying business uncertainty affect the price setting of firms and thus the real effects of monetary policy? A fundamental result of New Keynesian macroeconomics is that, due to price stickiness, changes in monetary policy affect real variables in the short run. If heightened uncertainty were to change the degree of price rigidity, this would directly influence monetary policy transmission. This channel is potentially important as in the recession of 2008/09, a time of great concomitant macroeconomic uncertainty, the average frequency of producer price changes increased by 7 percentage points compared to the pre-crisis average. Against this background the contribution of the present paper is threefold. First, we construct firm-specific expectation errors from IFO survey data for Germany and show that their absolut values are good proxies for idiosyncratic uncertainty. Second, we demonstrate that idiosyncratic uncertainty is a statistically significant, albeit economically rather insignificant determinant in the price setting behavior of firms. Third, we show in a New Keynesian dynamic stochastic general equilibrium (DSGE) model that monetary policy has smaller real effects in uncertain times. We also show that the effect on monetary policy transmission is quantitatively rather small.

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

The consequence of heightened uncertainty for the price-setting decisions of firms, however, has remained largely unexplored. In a recent contribution, Vavra (2013) matches an Ss price-setting model to CPI micro data and shows that idiosyncratic uncertainty affects the level of price rigidity and, through it, leads to time-varying effects of monetary policy. The focus on idiosyncratic (i.e. firm-specific) rather than aggregate uncertainty is justified as Boivin, Giannoni, and Mihov (2009), Golosov and Lucas (2007) as well as Klenow and Kryvtsov (2008) show that idiosyncratic shocks are the most important factor in explaining the price dynamics at the micro-level.[1] The key assumption to explain the effects of uncertainty is that firms face fixed costs in adjusting their prices. These costs create a region of inaction in which firms do not have an incentive to adjust their prices even if their charged price is not optimal. Heightened uncertainty in this framework has two effects. First, it widens the size of the region of inaction and induces more firms to "wait and see". Put differently, this effect makes prices more sticky. Second, heightened uncertainty is accompanied by a volatility effect as the variance of idiosyncratic shocks increases. This increase in the shock size pushes more firms outside the region of inaction in both directions. Consequently, we observe an increase in the frequency of price adjustment and in the price dispersion. Vavra (2013) analyzes the importance of both effects and shows that in his calibration the volatility effect dominates. Heightened uncertainty therefore triggers an increase in both the frequency of price adjustment and in price dispersion.

[1] Note the difference between idiosyncratic and aggregate uncertainty. The latter deals with aggregate shocks that affect all firms in the same way (see e.g. Basu and Bundick, 2012) whereas idiosyncratic uncertainty relates to shock processes that are firm-specific.

The novel contribution of this paper is to compute measures of firm-specific uncertainty and estimate directly the impact of heightened firm-level uncertainty on the firms' price setting behavior. These uncertainty measures are constructed from the confidential micro data in the IFO Business Climate Survey (IFO-BCS). Survey data are well-suited for our research question as they are likely to capture the uncertainty of actual decision-makers as opposed to outside experts. We use two different methods to construct these firm-specific uncertainty measures with different strengths and weaknesses. The first one follows Bachmann, Elstner, and Sims (2013) who construct expectation errors based on qualitative survey questions. We argue that the absolute expectation error is an appropriate measure for idiosyncratic uncertainty as it is strongly correlated with an expectation error dispersion measure. The advantage of these qualitative uncertainty measures is that they can be constructed on a relatively large sample of firms. However, they only allow us to evaluate the sign of the relationship between uncertainty and price setting at the firm-level. For a subset of firms we are, additionally, able to compute a quantitative measure in line with Bachmann and Elstner (2013) from firm statements concerning capacity utilization. With these quantitative uncertainty measures we directly evaluate the effect of idiosyncratic uncertainty on the price setting behavior of firms and use this elasticity as an input into a fully calibrated structural model. We also show that uncertainty measures based on either procedure are highly correlated, which gives us confidence that we are indeed measuring firm-level uncertainty.

The same micro data that allow us to construct the firm-specific uncertainty measures also have information on the price setting behavior of the same firms, which is a unique feature of the IFO-BCS.[2] To assess to what extent heightened firm-level uncertainty affects the frequency of price adjustment, we estimate a logit model on a panel of (on average) 2,500 German firms from January 1980 to December 2011 with firm-specific variables like business situation, capacity utilization, number of employees, and cost of input goods. We, in addition, incorporate our firm-level uncertainty measures. Our results suggest that heightened uncertainty increases the frequency of price changes. For example, the tripling of uncertainty during the recession of 08/09 – an increase of about 6 standard deviations – caused the average quarterly likelihood of a price change to increase from 31.6% to 32.1%. This means that indeed the volatility dominates the real options effect empirically. The finding is robust with respect to the choice of the uncertainty measure and the estimation specification.

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

Our results show that, even though idiosyncratic uncertainty was at the height of the 08/09-recession almost 8 percentage points higher than in normal times, the resulting effect on the frequency of price adjustment was rather small. During this time, a monetary stimulus of a 25 basis point cut in the nominal interest rate, would have lost about 1.2 percent of its effect on real output, with the impact effect decreasing

[2] One can think of the qualitative price statements of manufacturing firms as closely resembling the producer price index (PPI). The PPI is the appropriate measure for our study as Barsky, House, and Kimball (2007) show that it is the price stickiness of durable goods that is most relevant for monetary non-neutrality.

from 0.347% to 0.342%. However, while heightened uncertainty in isolation would not have led to a large increase in price flexibility in the 08/09-recession, we observe an overall increase in the average share of firms adjusting their price in a given quarter by almost 7 percentage points in the same time period. Such a sizable increase in price flexibility would have translated into a decline in the output impact effect of a 25 basis point monetary policy shock from 0.346% to 0.289%, a decrease of almost 17 percent. Hence, while changes in price flexibility over the business cycle are potentially an important issue for the conduct of monetary policy, they are unlikely to be driven by changes in firm-level uncertainty.

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

2 Measuring Idiosyncratic Uncertainty

In this section we describe the construction of idiosyncratic uncertainty measures from IFO Business Climate Survey (IFO-BCS) data. We construct both qualitative and quantitative measures based on firm specific production expectation errors.

2.1 IFO Business Climate Survey

The IFO Business Climate index is a much-followed leading indicator for economic activity in Germany. It is based on a firm survey which has been conducted since 1949. To the best of our knowledge it is the first business survey that started to ask manufacturing firms concerning their own output and price expectations (see Becker and Wohlrabe, 2008, for details). Since then the survey design of the IFO Business Climate index was 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 availability of micro data in a processable form we limit our analysis to the manufacturing sector from 1980 until 2011. Our analysis does not include East German firms.

An attractive feature of the IFO-BCS is the high number of participants. The average number of respondents at the beginning of our sample is approximately 5,000; towards the end the number is about half that at 2,300.[3] Participation in the survey is voluntary and there is some fraction of firms that are only one-time participants. However, conditional on staying two months in the survey, most firms continue to participate each month. In terms of firm size, the IFO-BCS contains all categories. About 9.4% of firms in our sample have less than 20 employees, roughly 32.0% have more than 20 but less than 100 employees, 47.3% employed between 100 and 1000 people, and 11.3% have a workforce of more than 1000.

The IFO-BCS is a monthly qualitative business survey that is supplemented on a quarterly basis with quantitative questions with respect to capacity utilization. In general, however, firms provide answers that fall into three main qualitative categories: *Increase*, *Decrease*, and a neutral category. In our analysis we focus on a wide range of explanatory variables that are relevant to the pricing decision of a firm. Table 1 summarizes these questions.

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

Table 1: Questionnaire

Number	Label	Question	Response categories		
MONTHLY QUESTIONS					
Q1	*Production*	Our domestic production activity with respect to product XY have ...	increased	roughly stayed the same	decreased
Q2	$E(Production)$	Expectations for the next 3 months: Our domestic production activity with respect to product XY will probably ...	increase	remain virtually the same	decrease
Q3	*Price*	Our net domestic sales prices for XY have ...	increased	remained about the same	gone down
Q4	$E(Price)$	Expectations for the next 3 months: Our net domestic sales prices for XY will ...	increase	remain about the same	decrease
Q5	*Business Situation*	We evaluate our business situation with respect to XY as ...	good	satisfactory	unsatisfactory
Q6	*Business Expectations*	Expectations for the next 6 months: Our business situation with respect to XY will in a cyclical view ...	improve	remain about the same	develop unfavourably
Q7	*Orders*	Our orders with respect to product XY have ...	increased	roughly stayed the same	decreased
QUARTERLY AND SUPPLEMENTARY QUESTIONS					
Q8	*Capacity Utilization*	The utilization of our production equipment for producing XY currently amounts to ... %.	30% ,40%,...,70%,75%,...,100%, more than 100%		
Q9	*Technical Capacity*	We evaluate our technical production capacity with reference to the backlog of orders on books and to orders expected in the next twelve months as ...	more than sufficient	sufficient	less than sufficient
Q10	*Employment Expectations*	Expectations for the next 3 months: Employment related to the production of XY in domestic production unit(s) will probably ...	increase	roughly stay the same	decrease
Q11	*Firmsize*	The number of employees in production for product XY corresponds to ...	1,2,...,1000,...,10000,...		

Notes: This table provides the translated questions and response possibilities of the IFO-BCS for manufacturing. For the production questions Q1 and Q2 firms are asked to ignore differences in the length of months or seasonal fluctuations. For Q8 customary full utilization is defined by 100%. Q11 is only asked once a year.

2.2 Construction of Qualitative Uncertainty Measures

The construction of ex-post forecast errors combines past responses of the production expectation question (Q2) with current responses of realized production changes vis-à-vis last month (Q1). We follow Bachmann et al. (2013). To fix ideas, imagine that the production expectation question in the IFO-BCS, Q2, was asked only for the next month instead of the following three months. In this case, when comparing the expectation in month $\tau-1$ with the realization in month τ, nine possibilities arise:[4] 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 reality, the production expectation question in the IFO-BCS is for three months ahead. Suppose that a firm stated in month $\tau-3$ that its production will increase in the next three months. Suppose further that in the next three months one observes the following sequence of outcomes: production increased between $\tau-3$ and $\tau-2$, remained unchanged between $\tau-2$ and $\tau-1$, and production decreased between $\tau-1$ and τ. Due to the qualitative nature of the IFO-BCS we have to make some assumptions about the

[4] In this section, the time index is defined as one month and denoted by τ.

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

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

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

cumulative production change over three months. As a baseline we adopt the following steps. First, we define for every 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.[5] Denote this variable by $REALIZ_{i,\tau}$. It can obviously range from $[-3,3]$. The expectation errors are then computed as described in Table 3.

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

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

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

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

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

The idea behind this measure is that firms realizing large expectation errors in period $\tau+3$, regardless of whether they are of a positive or negative nature, face high uncertainty in period τ. We analyze the importance of this timing decision in Section 5.

We also compute a measure of firm-level volatility based on Comin and Mulani (2006) as well as Davis, Haltiwanger, Jarmin, and Miranda (2006). Using a firm *i*'s expectation errors we can define a

[5] We also experiment with a weighted sum approach: we weight realizations in $\tau-2$ one half, realizations in $\tau-1$ one third and realizations in τ one sixth. Naturally, when asked in $\tau-3$ about the next three months, the firm may bias its answer towards the immediate future. None of our results depends on the precise weighting scheme.

symmetric 5-quarter rolling window standard deviation as

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

where $\overline{FE}^{qual}_{i,\tau}$ is the average of $FE^{qual}_{i,\tau+k}$ for $k = \{-3,0,3,6,9\}$.

2.3 Construction of Quantitative Uncertainty Measures

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

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

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-BCS. Taking the natural logarithm and the three-month difference, we get[6]

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

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

If the production capacity can be assumed not to have changed in the preceding quarter, and if 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. As a first pass we consider only firms which state in period $\tau-3$ that their production level (Q2), employment level, and technical production capacity will remain the same in the next three months.[7] We then compute $\Delta \log u_{i,\tau}$ three months later in τ. The

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

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

resulting measure $\Delta \log u_{i,\tau}$ constitutes our definition of a quantitative production expectation error, which we denote by $FE^{quan}_{i,\tau}$.

We then take the absolute value of $FE^{quan}_{i,\tau+3}$ to construct our quantitative measure of idiosyncratic uncertainty

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

where $ABSFE^{quan}_{i,\tau}$ denotes our quantitative idiosyncratic uncertainty measure of firm i in period τ. Note that we can compute quantitative uncertainty 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, however, makes it easier to interpret our empirical result with respect to the price setting of firms. We also compute a 5-quarter rolling window standard deviation denoted by $STDFE^{quan}_{i,\tau}$.

2.4 Discussion of Uncertainty Measures

Measuring idiosyncratic uncertainty is inherently difficult and, ideally, one would like to elicit from actual firm decision makers their subjective probability distributions over future events. With this data it would be straightforward to compute a measure of intrapersonal uncertainty. However, this type of data is usually not readily available,[8] and we, therefore, need to rely on proxies.[9]

Going forward, we will therefore use both the absolute firm's expectation error as well as the rolling window standard deviation of a firm's expectation errors as proxies for idiosyncratic uncertainty. However, one could argue that the absolute expectation error may also reflect unforeseen high first moment shocks and not only uncertainty per se. In this regard, Bachmann et al. (2013) discuss that dispersed forecast errors are likely driven by a higher variance of idiosyncratic shocks and not by an aggregate first moment shock. Therefore, in a first step, it is instructive to compare the properties of our proposed measure – the absolute expectation error – with those of an expectation error dispersion measure. To do so, the upper panel of Figure 1 plots the cross-sectional mean of $ABSFE^{qual}_{i,\tau}$, i.e. $MEANABSFE^{qual}_{\tau}$, together with the cross-sectional dispersion of expectation errors defined as

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

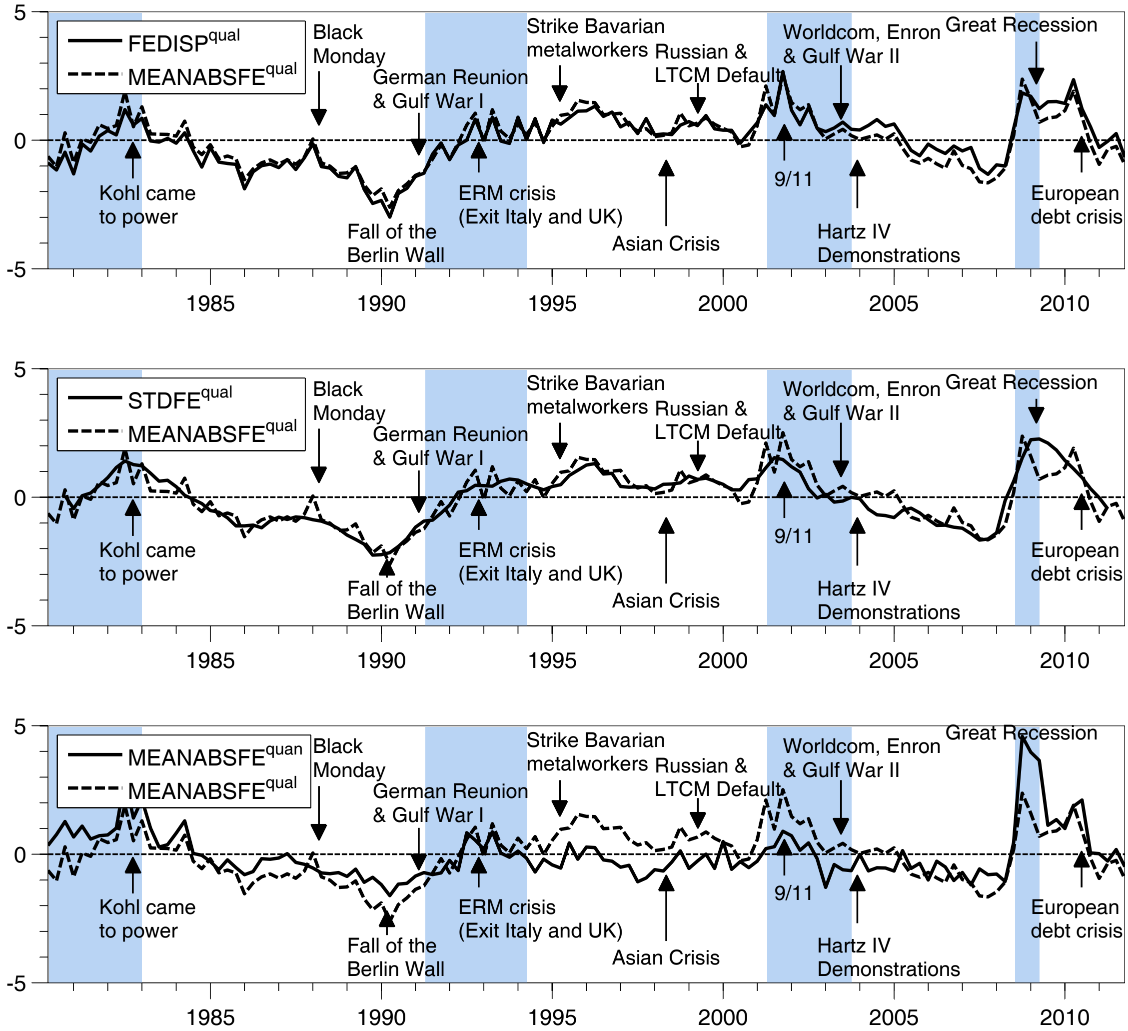
For better readability of the graphs, we only plot the last month of each quarter. Because of different measurement scales, we demean the series and normalize each by its standard deviation. The upper panel of Figure 1 shows that both time series display similar properties - they rise in the wake of the fall of the Berlin Wall, again around 2001, and at the start of the global financial crisis, where they remain elevated with the onset of the European debt crisis. All in all, we see a close link between both uncertainty proxies. The visual evidence is supported by the high time-series correlation coefficient of 0.94 between $FEDISP^{qual}_{\tau}$ and $MEANABSFE^{qual}_{\tau}$.

production change statements does not alter our results.

[8] To the best of our knowledge, there exist only two studies by Guiso and Parigi (1999) and Bontempi, Golinelli, and Parigi (2010) in which Italian firms are asked to provide such information. Their probability distributions, however, are not available repeatedly, at high frequency, or over long time horizons.

[9] This is common in the literature, e.g. Gilchrist et al. (2010) and Leahy and Whited (1996) use information from financial markets to determine idiosyncratic uncertainty for firms.

Figure 1: Measures of Idiosyncratic Uncertainty



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

Further evidence that $ABSFE_{i,\tau}^{qual}$ is an appropriate measure for idiosyncratic uncertainty comes from disaggregating the time series and analyzing the time-series correlation coefficients of $MEANABSFE_{\tau}^{qual}$ and $FEDISP_{\tau}^{qual}$ for 13 manufacturing industries and 5 firm-size classes separately. The results are summarized in the first two columns of Table 11 in Appendix A. All industrial sectors and firm-size classes feature correlation coefficients that are around 0.9 or higher.

The middle panel of Figure 1 shows the cross-sectional mean of $STDFE_{i,\tau}^{qual}$ together with $MEANABSFE_{\tau}^{qual}$. Both time series comove closely with a high positive time-series correlation coefficient of 0.86. Although this strong relationship decreases somewhat at the disaggregate level, most correlations are still in the range of 0.6 and 0.8 (see the last two columns of Table 11 in Appendix A). This strong relationship also holds at the firm level: here we find a pooled Spearman correlation coefficient between $ABSFE_{i,\tau}^{qual}$ and $STDFE_{i,\tau}^{qual}$ of 0.47.[10]

The link between the qualitative and the quantitative absolute expectation error is illustrated in the lower panel of Figure 1 where we plot the cross-sectional mean of $ABSFE_{i,\tau}^{quan}$ ($MEANABSFE_{\tau}^{quan}$) together with $MEANABSFE_{\tau}^{qual}$. Both proxies for idiosyncratic uncertainty move reasonably close to each other. The unconditional time-series correlation coefficient between $MEANABSFE_{\tau}^{quan}$ and $MEANABSFE_{\tau}^{qual}$ is 0.62. At the firm level we find a pooled Spearman correlation coefficient between $ABSFE_{i,\tau}^{qual}$ and $ABSFE_{i,\tau}^{quan}$ of 0.65. $MEANABSFE_{\tau}^{qual}$ and $MEANABSFE_{\tau}^{quan}$ are strongly positively correlated with $FEDISP_{\tau}^{qual}$. Furthermore, all measures are countercyclical: their pairwise time-series unconditional correlation coefficients with quarter-to-quarter growth rates of production, total hours worked and employment in the West German manufacturing sector are negative (see Table 4).

Table 4: Cross-Correlations

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

Notes: This table shows the pairwise unconditional time-series correlation coefficients of various activity variables in West German manufacturing together with different measures of idiosyncratic uncertainty. Specifically, the activity variables are quarter-on-quarter growth of production ($\Delta \log Production$), total hours worked ($\Delta \log Hours$) and employment ($\Delta \log Employment$). Note that the number of observations for $STDFE^{quan}$ is quite small. The data sources are the Federal Statistical Office and Eurostat. All variables are seasonally adjusted. The sample period is I/1980 - IV/2011.

Table 5 provides summary statistics of our uncertainty proxies for all observations over the entire pooled cross-section. It is evident that the number of observations is much larger for our qualitative uncertainty measures compared to the quantitative ones. Specifically, the total number of observations decreases to 8,731 for the case of $STDFE_{i,\tau}^{quan}$. Further we observe that the standard deviation of the 5-quarter rolling window standard deviation is much lower compared to the corresponding measure of the absolute expectation error. Finally, the mean and standard deviation of $ABSFE_{i,\tau}^{quan}$ are 4.8 and 11.1 percent, respectively. The first number is in the range of the findings of Bloom et al. (2012). The latter number provides a sense of the idiosyncratic shifts in uncertainty.

3 Empirical Analysis

In this section we analyze the effects of heightened idiosyncratic uncertainty on the frequency of price adjustment. We first the construct the variables and specify the empirical model. We then present the results.

[10]For the quantitative expectation errors we determine a pooled Pearson correlation coefficient of 0.69.

Table 5: Summary Statistics Pooled Cross-Section

Statistics	$ABSFE^{qual}_{i,\tau}$	$ABSFE^{quan}_{i,\tau}$	$STDFE^{qual}_{i,\tau}$	$STDFE^{quan}_{i,\tau}$
Obs.	362,169	90,385	251,019	8,731
Mean	0.623	0.048	0.721	0.016
Std.Dev.	0.849	0.111	0.480	0.049
Percentiles				
5%	0.000	0.000	0.000	0.000
10%	0.000	0.000	0.000	0.000
25%	0.000	0.000	0.400	0.000
50%	0.000	0.000	0.748	0.000
75%	1.000	0.057	1.020	0.000
90%	2.000	0.154	1.356	0.047
95%	2.000	0.223	1.497	0.086

Notes: This table provides summary statistics of $ABSFE^{qual}_{i,t}$, $ABSFE^{quan}_{i,t}$, $STDFE^{quan}_{i,t}$, and $STDFE^{qual}_{i,t}$ of all observations over the entire pooled cross-section. The sample period is I/1980 - IV/2011.

3.1 Construction of Price Variables

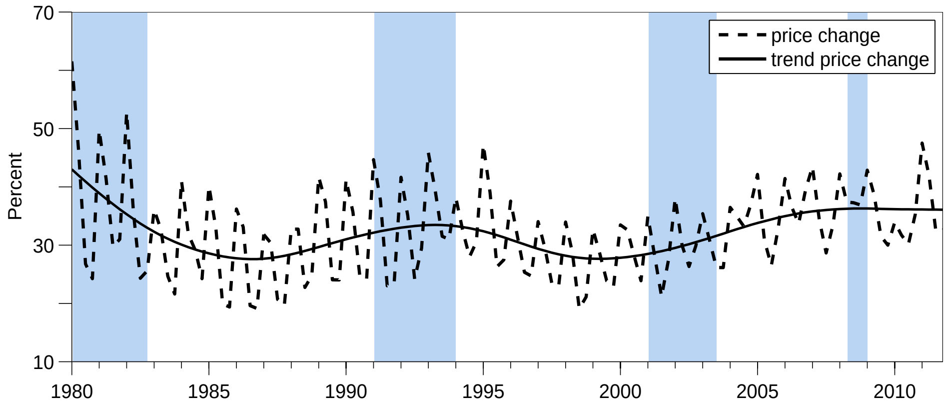
Although the IFO-BCS includes price statements at the monthly frequency, other variables used in this approach such as capacity utilization are only available on a quarterly basis. We therefore estimate a quarterly model. Thus, we need to transform the monthly price statements to a quarterly frequency. The new 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.[11]

Figure 2 provides a graphical illustration of our new price variable. The figure plots the frequency of price changes (dashed line), i.e. the share of firms that have adjusted their price in a given quarter, together with the HP-filtered trend of the frequency of price changes (solid line). The trend of price adjustments moves in a band between 25% and 45% and suggests that on average roughly one third of all firms adjust their prices each quarter. Concerning business cycle properties we find that the frequency of price changes on average is somewhat higher during recessions (34%) than in normal times (31%). This is in line with the findings of Vavra (2013) who finds a modest positive correlation between the frequency of price changes and recessions for the U.S.[12]

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

[12] We find in a regression on seasonal and recession dummies, as dated by the Economic Cycle Research Institute (ECRI), that during recessions the frequency of price adjustment is 2.6 percentage points higher for *quarterly* data. This number increases to 7.2 percentage points by considering only the recession of 08/09. In particular this recession was characterized by heightened idiosyncratic uncertainty (see Figure 1). In a similar exercise Vavra (2013) finds that during recessions the frequency of price adjustment is 1.2 percentage points higher for *monthly* CPI data.

Figure 2: Frequency of Price Changes



Notes: The figure shows the frequency of price changes and the HP-filtered trend of the frequency of price changes. All data is on a quarterly basis. Shaded regions show recessions as dated by the Economic Cycle Research Institute (ECRI): I/1980 - IV/1982, I/1991 - II/1994, I/2001 - III/2003 and II/2008 - I/2009.

3.2 Specification of the Empirical Model

We employ a quarterly logit model to estimate the probability of observing a price change, i.e.

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

where $y_{i,t}$ is the dependent variable, the vector $\mathbf{x}_{i,t}$ includes all explanatory variables, and $\mathbf{b}$ is the coefficient vector.[13] To account for the panel structure of the data, standard errors are clustered by firm.

Table 6 lists the variables used in the estimation procedure. 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 the respective firm adjusted its price was two quarters ago. In addition, seasonal dummies are introduced, to take into account that adjustments of prices might be more frequent in a certain season. The benchmark is the first quarter, *Spring* stands for the second, *Summer* for the third, and *Fall* for the fourth quarter. We add sector-fixed effects to control for heterogeneity across sectors. As a proxy for macroeconomic variables, we add time dummies for each quarter (Time-fixed effects). The Time-fixed effects capture aggregate shocks which influence all firms' prices in the same way but also control for unobserved variables that might influence prices and uncertainty at the same time.

Firm-specific variables comprise information that we have on the condition of a specific firm and are proxies for its state.[14] The variables we use are presented in Table 6. The second column presents the name of the variable, the third column shows the response possibilities. At the heart of this paper are the uncertainty measures that are described in detail in Section 2. We use two qualitative uncertainty proxies ($ABSFE^{qual}$ and $STDF^{qual}$) and two quantitative measures ($ABSFE^{quan}$ and $STDF^{quan}$). To account for

[13] As asymmetries might be important in price-setting behavior, we follow Lein (2010) and estimate two additional specifications that separately model the probability of a price increase and decrease. We find that heightened uncertainty leads to a rise in price dispersion, i.e. it increases both the probability increase as well as a decrease in prices. Detailed results are presented in Appendix D.

[14] One can argue that there is an indirect effect of uncertainty on price setting: Uncertainty may lead to a postponing of projects, that is demand for certain goods decreases, this in turn has an effect on price setting. This indirect effect is accounted for with the choice of our firm-specific variables, in particular the variable Orders.

Table 6: Description of Variables

Label	Variable	Response	Scale
Seasonal dummies	$Spring/Summer/Fall$		Binary
Taylor dummies	$Taylor1 - Taylor8$		Binary
Sector dummies	$Sector1 - Sector14$		Binary
Capacity Utilization	$Capacity\ utiliz.$	30%, 40%...70%, 75%, 80%...100%...	Interval
Firmsize	$\log(Firmsize)$	0...11.8	Interval
Cost of Input Goods	$\Delta Costs$	−0.42...0.87	Interval
Business Situation	$Statebus^{+}$	good	Binary
	$Statebus^{-}$	unsatisfactory	Binary
Business Expectation	$Expbus^{+}$	increase	Binary
	$Expbus^{-}$	decrease	Binary
Orders	$Order^{+}$	increase	Binary
	$Order^{-}$	decrease	Binary
Technical Capacity	$Tech.capacity^{+}$	more than sufficient	Binary
	$Tech.capacity^{-}$	less than sufficient	Binary
Expected Employees	$Expempl^{+}$	increase	Binary
	$Expempl^{-}$	decrease	Binary
Time-fixed effects	$Time1\ldots$		Binary
Qualitative idiosyncratic uncertainty	$ABSFE^{qual}$	0,1,2,3,4	Ordinal
Quantitative idiosyncratic uncertainty	$ABSFE^{quan}$	0%...200%	Interval
Qualitative idiosyncratic uncertainty	$STDFE^{qual}$	0...3.38	Interval
Quantitative idiosyncratic uncertainty	$STDFE^{quan}$	0...0.75	Interval
Price change in last 3 months	$Price\ change$	Change	Binary

Notes: For the construction of the Cost of Input Goods variable, see Appendix B.

possible asymmetric effects of a number of micro variables we follow Lein (2010) and include variables with both positive and negative values separately. For example, firms are asked to appraise their current state of business which is divided into two sub-variables. If firm i at time t reports that its state is good, the variable $Statebus^{+}_{i,t}$ is equal to one, and the variable $Statebus^{-}_{i,t}$ is equal to zero. By contrast, 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 similarly with Business Expectations, Orders, Technical Capacity and Expected Employees. Note that the variable Orders asks whether orders changed versus the previous month; the quarterly generated variable $Order^{+}_{i,t}$ ($Order^{-}_{i,t}$) takes the value one if firm i states that its orders increased (decreased) in at least one of the previous three months. Lein (2010) emphasizes the important role of the firms' costs for intermediate goods as determinant of the price setting of firms. The IFO-BCS contains no information about costs, therefore we construct a variable that proxies the change in the cost of input goods for each sector k for each time period ($\Delta Costs_{k,t}$) following Schenkelberg (forthcoming). $\Delta Costs_{k,t}$ for each sector is calculated as the weighted average of net price changes of (input) goods from all sectors. The weights are derived from the relative importance of the sectors in the production of goods in sector k.[15]

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.

3.3 Results

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

The table reports marginal effects. Quantitative variables (*Capacity utiliz.*, $ln(Firmsize)$, $\Delta Costs$, $ABSFE^{qual}$, $ABSFE^{quan}$, $STDFE^{qual}$, and $STDFE^{quan}$) are evaluated at their respective sample averages. Qualitative variables are evaluated at zero, i.e. "satisfactory" ($Statebus^{+}$, $Statebus^{-}$), "remain about the same" ($Expbus^{+}$, $Expbus^{-}$, $Expempl^{+}$, $Expempl^{-}$), "roughly stayed the same" ($Orders^{+}$, $Orders^{-}$), or "sufficient" ($Tech.\ capacity^{+}$, $Tech.\ capacity^{-}$). Marginal effects for the dummy variables are calculated as the difference in the probability of a price change as the dummy switches from 0 to 1. Due to brevity marginal effects for the time-fixed effects, the sector-specific dummies, seasonal dummies, Taylor dummies and a number of firm-specific variables are omitted from the table.[16] The timing of uncertainty is such that the *realized* expectation errors at date *t+1* do not constitute uncertainty in *t+1*, but in *t*. For example, the firm forecasts its production in the first quarter, in the second quarter it knows its actual production during the first quarter. From these two observations we are able to calculate a forecast error. This error – which is computed in the second quarter – proxies uncertainty of the firm in the first quarter.

In line with the literature, the major determinant of price setting are the costs of intermediate goods that firms face, with higher costs increasing the probability of a price change by 0.1 to 0.3 percentage points. Both good and unsatisfactory current business situations, increasing and decreasing business expectations and order levels as well as a higher capacity utilization lead to a higher probability of price change.

Most relevant for our exercise: Regardless of the way uncertainty is measured and of the inclusion of firm-specific variables, higher uncertainty increases the probability of a price change. The signs of the marginal effects of $ABSFE^{qual}$ show that higher uncertainty increases the probability of a price change,

[15]See Appendix B for a detailed description.
[16]Supplementary results are shown in Table 13 in Appendix C.

Table 7: Benchmark Results (Pooled Logit Model) for Price Change

Dependent variable: Price change								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$ABSFE^{qual}$	0.013***				0.007***			
	(0.001)				(0.002)			
$ABSFE^{quan}$		0.094***				0.076***		
		(0.019)				(0.025)		
$STDFE^{qual}$			0.043***				0.020***	
			(0.003)				(0.003)	
$STDFE^{quan}$				0.217				0.031
				(0.135)				(0.122)
Capacity utiliz.					0.001***	0.002***	0.001***	0.001
					(0.000)	(0.000)	(0.000)	(0.001)
Δ Costs					0.215***	0.292***	0.078***	0.027
					(0.022)	(0.042)	(0.022)	(0.088)
$Statebus^{+}$					0.035***	0.041***	0.028***	0.060***
					(0.004)	(0.007)	(0.004)	(0.020)
$Statebus^{-}$					0.048***	0.065***	0.038***	0.055*
					(0.004)	(0.009)	(0.004)	(0.033)
$Expbus^{+}$					0.020***	0.020**	0.011***	0.007
					(0.004)	(0.009)	(0.004)	(0.023)
$Expbus^{-}$					0.058***	0.041***	0.050***	0.011
					(0.004)	(0.009)	(0.004)	(0.021)
$Orders^{+}$					0.076***	0.063***	0.061***	0.063***
					(0.004)	(0.007)	(0.004)	(0.022)
$Orders^{-}$					0.060***	0.045***	0.045***	0.072***
					(0.004)	(0.007)	(0.004)	(0.023)
Test for joint significance (χ^2-Test:)								
Sector dummies	802.52***	262.80***	605.75***	32.83***	600.20***	194.51**	513.51***	28.23***
Taylor dummies	8318.52***	2944.14***	9878.63***	599.00***	7103.42***	2671.07***	8145.65***	515.31***
Time-fixed effects	5390.27***	1712.49***	2328.18***	228.99***	2433.48***	795.64***	1251.91***	228.24***
Observations	249,363	62,982	210,864	6,960	195,605	54,674	167,918	6,208
Pseudo R-squared	0.120	0.131	0.135	0.197	0.134	0.138	0.146	0.208

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

Notes: The table presents marginal effects for a choice of firm-specific variables. Robust and clustered (by firm) standard errors are in parentheses. Included in the pooled logit model but not shown in the table are time-fixed effects for each quarter, sector-specific dummies, seasonal dummies and Taylor dummies. Models (5)-(8) include, in addition, all firm-specific variables described in Table 6. $ABSFE^{qual}$: qualitative idiosyncratic uncertainty; $ABSFE^{quan}$: quantitative idiosyncratic uncertainty; $STDFE^{qual}$: 5-quarter rolling window standard deviation of a firm's qualitative expectation errors; $STDFE^{quan}$: 5-quarter rolling window standard deviation of a firm's quantitative expectation errors; χ^2-Test is a test of whether the respective coefficients are jointly zero.

both in the estimation with only a small number of regressors, Column (1), as well as with all of the regressors, Column (5). Unfortunately, the size of these marginal effects cannot be interpreted. To gauge the size of this effect, we turn to the quantitative proxy $ABSFE^{quan}$. Here, the marginal effects imply that prices are about 0.1 percentage points more likely to change when our measure of uncertainty changes by one percentage point. To put this result into perspective, note that the micro-level standard deviation of $ABSFE^{quan}$ is about 11 percent (see Table 5). Relevant for monetary policy, however, are shifts in the average idiosyncratic uncertainty. Here, we observed in the recent financial crisis that uncertainty increased by eight percentage points. Turning to the rolling window proxies, we find that the marginal effects for $STDFE^{qual}$ are similarly positive as the results obtained from $ABSFE^{qual}$. This is in support of our hypothesis that the mean absolute expectation error is a good proxy for idiosyncratic uncertainty. The marginal effects of $STDFE^{quan}$ are positive but statistically insignificant. This is due to the fact that the number of observations is small compared to all other regressions.

To sum up, we find that the price setting behavior of firms is influenced by time- and state-dependent factors. Changes in input costs are the most important determinant. However, idiosyncratic uncertainty seems to be a relevant factor for price decisions as well.[17]

4 Model Evidence

4.1 New Keynesian DSGE model

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

4.1.1 Households

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

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

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

[17] Results for an alternative estimation with a panel fixed effects model are shown in Table 9 in Section 5.

the following budget constraint

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

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

4.1.2 Final Good Firms

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

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

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

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

4.1.3 Intermediate Good Firms

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

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

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

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

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

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

4.1.4 Monetary Policy

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

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

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

4.1.5 Calibration

We calibrate the log-linearized model using standard values from Galí (2008). Table 8 presents the calibrated parameter values. The model period is one quarter. The parameter ψ is chosen such that the representative household devotes one third of his time to work. For the experiments following in the next subsection, we set the baseline sample to 1980Q1-2008Q1, i.e. ending before the recession of 08/09. In this time span, on average 31.63% of firms adjust their price in a given quarter, corresponding to a Calvo parameter, θ, of 0.684.

Table 8: Parameter Values

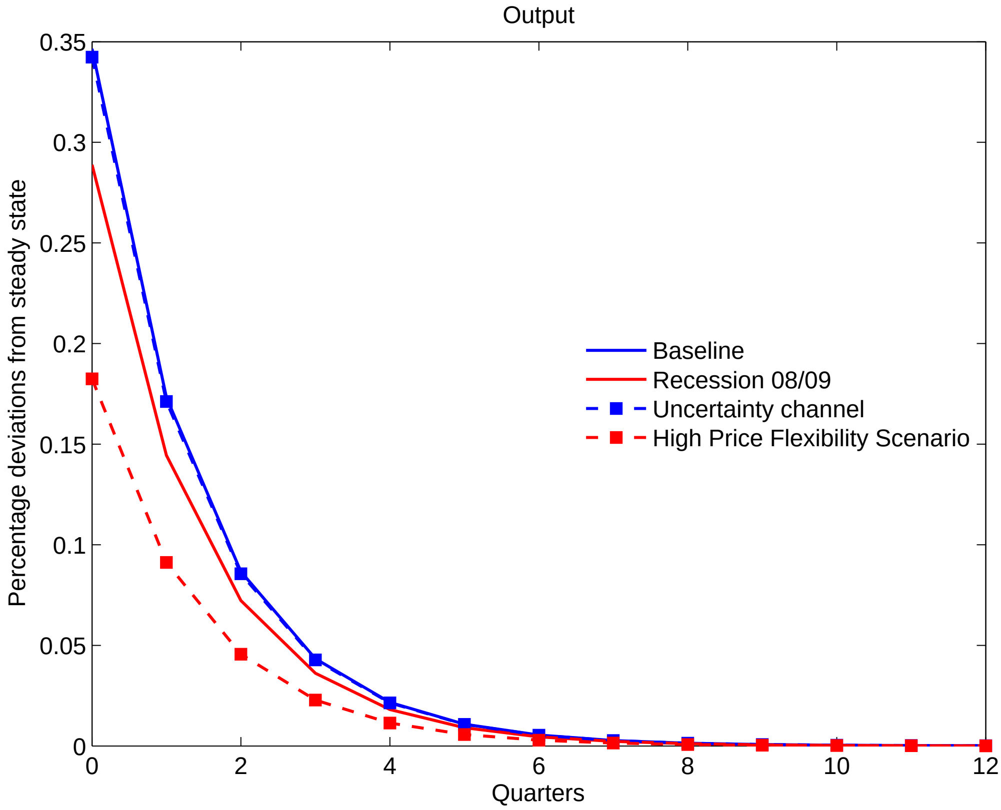
Parameter		Value
Steady state inflation rate	$\overline{\pi}$	1
Discount Factor	β	0.99
Constant relative risk aversion	σ	1
Inverse elasticity of labor supply	ϕ	1
Labor disutility	ψ	5
Elasticity of substitution	ε	6
Calvo parameter (baseline)	θ	0.684
Returns to scale	$1-\alpha$	0.67
Taylor rule coefficient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

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

Using our New Keynesian business cycle model, we are now able to conduct a number of experiments to flesh out the connection between firm-level uncertainty, price flexibility, and the effectiveness of monetary policy. In our baseline economy, a 25 basis point monetary policy shock leads, on impact, to a 0.3465 percent deviation of output from its steady state (blue line in Figure 3), which is in line with the findings of, e.g., Christiano, Eichenbaum, and Evans (2005) and Smets and Wouters (2007). During the 08/09-recession, the average share of firms adjusting their price in a given quarter increased by almost 7 percentage points to 38.6%, translating to a θ of 0.614. In this environment, a 25 basis point monetary policy shock has an impact multiplier of 0.2889, i.e. monetary policy loses almost 17% of its effect on output compared to the baseline scenario (red line in Figure 3).

Our microeconometric analysis enables us to quantify how much of this loss in effectiveness is directly attributable to an increase in firm-level uncertainty. Our quantitative measure of uncertainty, $ABSFE^{quan}$, has a non-recession sample (1980Q1-2008Q1) mean of 4.3. In the third quarter of 2008, right at the height of the financial crisis, our measure reaches its sample maximum of 12.3, an increase of 8 percentage points. We can use our empirical model to compute the change in the probability of a price-adjustment due to this unforeseen, permanent, once and for all increase in uncertainty and translate it into a reduction

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



Notes: Solid blue line: baseline price flexibility ($\theta = 0.684$); solid red line: increased price flexibility in 08/09 recession ($\theta = 0.614$); dashed blue line with squares: increased price flexibility attributed to increase in uncertainty in 08/09 recession ($\theta = 0.679$); dashed red line with squares: scenario where increase in price flexibility is thrice that in the 08/09 recession ($\theta = 0.475$). Horizontal axis indicates quarters. Vertical axis measures percentage deviations from steady state.

in the Calvo parameter of 0.005.[18] The dashed blue line with squares in Figure 3 shows the response of the output in this high uncertainty environment to a 25 basis point monetary policy shock. The response is hardly distinguishable from the response of the baseline model. The impact multiplier is now 0.3424, only 1.2% lower than in the baseline environment. We can conclude that it is not the uncertainty channel that is at the heart of the increase in price flexibility and the subsequent loss in effectiveness of monetary policy.

Taking a time of very low price flexibility in our sample, e.g. 1998Q3, and comparing it to a time when firms were changing prices much more rapidly, say 2008Q3, we find that the difference in the average share of firms adjusting their price in a given quarter is about 20 percentage points or about thrice the increase in price flexibility during the recession of 08/09. We use this number to get a rough estimate of the maximum change in monetary non-neutrality in our sample. The resulting impulse response function of output to a 25 basis point monetary policy shock in this time of extremely high price flexibility is shown in Figure 3 (dashed red line with squares). The impact deviation of output from its steady state is now only 0.1825, more than 47% lower than in our baseline calibration. This number is close to the 55%-loss in the effectiveness of monetary policy that Vavra (2013) finds between times of high and low volatility, but we do not find evidence for uncertainty being a major driver of this loss of monetary non-neutrality.

[18]Specifically, we first re-estimate the empirical baseline model on the 1980Q1-2008Q1 sample. We then compute the marginal effects of uncertainty at the non-recession mean of 4.3 and the 08/09-recession peak of 12.3, thus taking non-linearities into account. The difference in marginal effects then directly translates into the change of the Calvo parameter.

5 Robustness Checks

The results of our econometric baseline model show that the probability of price adjustment increases by 0.076 percentage points when uncertainty rises by one percentage point as measured by the absolute expectation errors (see the sixth column in the upper panel of Table 9). We now conduct a battery of robustness checks. First, we re-estimate our empirical model employing a panel fixed-effects logit estimator. This allows us to better control for firm-specific effects that potentially bias our results. The fixed-effects estimator delivers marginal effects for the quantitative uncertainty proxies that are smaller than the baseline case (see the second panel of Table 9). The signs, however, remain positive and are often significant. For the empirical model (6), using $ABSFE^{quan}$ and controlling for all firm-specific variables, we obtain a marginal effect of 0.042.[19] Overall, the fixed-effects model suggests that heightened uncertainty has smaller positive effects on price adjustment compared to our baseline results.[20]

The next robustness check concerns the timing of the uncertainty proxies. This timing decision is especially important for the uncertainty measures $ABSFE^{qual}$ and $ABSFE^{quan}$. Constructing our baseline uncertainty proxies, we use the realized expectation error in $t+1$ to measure uncertainty at time t.2 The idea is that a realized expectation error in $t+1$ indicates that a firm was uncertain at the period of expectation formation in time t. One could argue, however, that a firm becomes more uncertain after the realization of an expectation error. Therefore, we now change the timing of uncertainty such that the realized expectation errors at date $t+1$ constitute uncertainty in $t+1$ and not in t. Note that this alternative timing should increase the effects of uncertainty as the effect of the larger shock materialization is now picked up by our measure of uncertainty. And this notion is indeed supported by our estimates, for both the quantitative and the qualitative measure we find marginal effects that are twice as large as those of the baseline model.

The third robustness check deals with the possibility that price changes today were already planned in the past. Today's prices may not, therefore, react to current events. This issue is also supported by the fact that 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 leave out price changes that are already anticipated in the past, that is price changes that are already set in the past (in some pricing plan); 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). Consequently, in this exercise, we concentrate on price changes that are completely unexpected and see whether they react to idiosyncratic uncertainty. With a value of 0.052, the marginal effect of the quantitative measure is smaller than that of the baseline model. Marginal effects of the qualitative measures are half the size of the baseline result.

The final two robustness checks only concern the qualitative measures of uncertainty, $ABSFE^{qual}$ and $STDFE^{qual}$. For both proxies we are able to compute numbers at a monthly frequency. Hence, we first redo our baseline estimations with monthly data by excluding the quarterly supplementary questions such as capacity utilization (Q8), employment expectations (Q9) and assessment of technical capacities (Q10).[21]

[19] We do not report marginal effects for $STDFE^{quan}$ as the fact that more than 75% of observations are zero (see Table 5) is problematic for the fixed-effects estimator, given the lower number of observations.

[20] Using a linear fixed-effects estimator does not considerably change these results.

[21] For $STDFE^{qual}$ we face the problem of dealing with expectation errors that have overlapping forecast horizons. We therefore compute $STDFE^{qual}$ by using the same timing as in equation (2). Note that we are still able to construct values for $STDFE^{qual}$ at a monthly frequency.

The results are shown in the upper panel of Table 10. We find that heightened uncertainty also increases the probability of a price change at a monthly level which supports our baseline results.

In the last exercise, we redefine $ABSFE^{qual}$. In the baseline model we make implicit statements with respect to the size of the firms' forecast errors although both production expectations and realizations are ordinal variables. Here, we construct a simpler qualitative uncertainty measure that just takes the value one at time t if there is a realized expectation error in $t+1$. The results are robust to using this simple qualitative uncertainty proxy.

6 Conclusion

The contributions of this paper are threefold. First, using micro data from German manufacturing firms provided by the IFO-BCS, we show that the absolute forecast error of a firm is a good proxy for the idiosyncratic uncertainty of that particular firm. The high correlation between the absolute forecast errors and the forecast error dispersion – both at the aggregate and at the disaggregate level – shows that the absolute expectation error does not reflect unforeseen high first moment shocks. Second, we find that idiosyncratic uncertainty increases the frequency of price adjustment. Third, the total quantitative impact of idiosyncratic uncertainty on the frequency of price adjustment of firms is rather small. Monetary policy therefore does not lose much of its effectiveness on real output.

This last point is particulary important for economic decision makers. Recent evidence points to uncertainty playing a role in the decision-making process of central bankers, e.g. Kohlhas (2012) finds that U.S. monetary policy seem to be more active in uncertain times. Our analysis, however, shows that the role of heightened uncertainty should be of minor concern for the conduct of monetary policy. While we focus on price rigidities, in future work it might be worthwhile to explore other possible propagation mechanisms of heightened uncertainty.

Table 9: Robustness Checks

Dependent variable: Price change								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Baseline Results (Pooled Logit Model)								
$ABSFE^{qual}$	0.013***				0.007***			
	(0.001)				(0.002)			
$ABSFE^{quan}$		0.094***				0.076***		
		(0.019)				(0.025)		
$STDFE^{qual}$			0.043***				0.020***	
			(0.003)				(0.003)	
$STDFE^{quan}$				0.217				0.031
				(0.135)				(0.122)
Panel fixed-effects logit estimation								
$ABSFE^{qual}$	0.026***				0.003**			
	(0.006)				(0.002)			
$ABSFE^{quan}$		0.056**				0.042		
		(0.026)				(0.026)		
$STDFE^{qual}$			0.042***				0.024***	
			(0.003)				(0.004)	
$STDFE^{quan}$				–				–
Uncertainty proxy at time of realization (Pooled Logit Model)								
$ABSFE^{qual}$	0.025***				0.010***			
	(0.001)				(0.002)			
$ABSFE^{quan}$		0.222***				0.143***		
		(0.023)				(0.026)		
$STDFE^{qual}$			0.038***				0.015***	
			(0.003)				(0.003)	
$STDFE^{quan}$				0.023				-0.158
				(0.119)				(0.110)
Unexpected Price Changes (Pooled Logit Model)								
$ABSFE^{qual}$	0.007***				0.004***			
	(0.001)				(0.001)			
$ABSFE^{quan}$		0.071***				0.052***		
		(0.014)				(0.015)		
$STDFE^{qual}$			0.025***				0.017***	
			(0.003)				(0.002)	
$STDFE^{quan}$				0.065				0.008
				(0.073)				(0.061)

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

Notes: The table presents marginal effects for different uncertainty proxies. Robust and clustered (by firm) standard errors are in parentheses. Included in all models but not shown in the table are time-fixed effects for each quarter, sector-specific dummies, seasonal dummies and Taylor dummies. Models (5)-(8) include, in addition, all firm-specific variables described in Table 6. $ABSFE^{qual}$: qualitative idiosyncratic uncertainty; $ABSFE^{quan}$: quantitative idiosyncratic uncertainty; $STDFE^{qual,realiz}$: 5-quarter rolling window standard deviation of a firm's qualitative expectation errors; $STDFE^{quan,realiz}$: 5-quarter rolling window standard deviation of a firm's quantitative expectation errors. For the case of the of the fixed-effects logit estimator, we do not report marginal effects for $STDFE^{quan}$ as the fact that more than 75% of observations are zero (see Table 5) is problematic for the fixed-effects estimator, given the lower number of observations.

Table 10: Robustness Checks II

Dependent variable: Price change				
	(1)	(2)	(3)	(4)
Estimations on a monthly level (Pooled Logit Model)				
$\text{ABSFE}^{\text{qual}}$	0.008***		0.010***	
	(0.001)		(0.001)	
$\text{STDFE}^{\text{qual}}$		0.049***		0.026***
		(0.003)		(0.004)
Uncertainty proxy as dummy variable (Pooled Logit Model)				
$\text{ABSFE}^{\text{qual}}$	0.018***		0.009***	
	(0.002)		(0.003)	

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

Notes: The table presents marginal effects for the uncertainty proxy estimated from monthly observations in the first panel. The second panel provides results for a binary uncertainty proxy. Robust and clustered (by firm) standard errors are in parentheses. Included in the pooled logit model but not shown in the table are time-fixed effects for each quarter, sector-specific dummies, seasonal dummies and Taylor dummies. Models (3) and (4) include, in addition, all firm-specific variables described in Table 6 except *Capacity Utilization*, *Technical Capacity* and *Expected Employees* which are all at a quarterly frequency. $ABSFE^{qual}$: quantitative idiosyncratic uncertainty; $STDFE^{qual}$: 5-quarter rolling window standard deviation of a firm's qualitative expectation errors.

References

Arellano, C., Bai, Y., Kehoe, P. J., 2012. Financial frictions and fluctuations in volatility. Federal Reserve Bank of Minneapolis Research Department Staff Report 466.

Bachmann, R., Bayer, C., 2012. 'Wait-and-see' business cycles?, mimeo.

Bachmann, R., Elstner, S., 2013. Firms' optimism and pessimism, mimeo.

Bachmann, R., Elstner, S., Sims, E. R., 2013. Uncertainty and economic activity: Evidence from business survey data. American Economic Journal: Macroeconomics.

Barsky, R. B., House, C. L., Kimball, M. S., June 2007. Sticky-price models and durable goods. American Economic Review 97 (3), 984–998.

Basu, S., Bundick, B., 2012. Uncertainty shocks in a model of effective demand, mimeo.

Becker, S., Wohlrabe, K., 2008. Micro data at the ifo institute for economic research - the 'ifo business survey' usage and access. Schmollers Jahrbuch 128, 307–319.

Bloom, N., 2009. The impact of uncertainty shocks. Econometrica 77 (3), 623–686.

Bloom, N., Floetotto, M., Jaimovich, N., Saporta-Eksten, I., Terry, S. J., 2012. Really uncertain business cycles. NBER Working Papers 18245.

Boivin, J., Giannoni, M. P., Mihov, I., 2009. Sticky prices and monetary policy: Evidence from disaggregated us data. American Economic Review 99 (1), 350–384.

Bontempi, M., Golinelli, R., Parigi, G., 2010. Why demand uncertainty curbs investment: Evidence from a panel of italian manufacturing firms. Journal of Macroeconomics 32 (1), 218–238.

Calvo, G. A., 1983. Staggered prices in a utility-maximizing framework. Journal of Monetary Economics 12 (3), 383–398.

Christiano, L., Motto, R., Rostagno, M., May 2010. Financial factors in economic fluctuations. ECB Working Paper Series 1192.

Christiano, L. J., Eichenbaum, M., Evans, C. L., 2005. Nominal Rigidities and the Dynamic Effects of a Shock to Monetary Policy. Journal of Political Economy 113 (1), 1–45.

Comin, D., Mulani, S., May 2006. Diverging trends in aggregate and firm volatility. The Review of Economics and Statistics 88 (2), 374–383.

Davis, S. J., Haltiwanger, J. C., 1992. Gross job creation, gross job destruction, and employment reallocation. Quarterly Journal of Economics 107 (3), 819–863.

Davis, S. J., Haltiwanger, J. C., Jarmin, R., Miranda, J., 2006. Volatility and dispersion in business growth rates: Publicly traded and privately held firms. NBER Macroeconomics Annual.

Doms, M., Dunne, T., 1998. Capital adjustment patterns in manufacturing plants. Review of Economic Dynamics 1 (2), 409–429.

Galí, J., 2008. Monetary Policy, Inflation, and the Business Cycle: An Introduction to the New Keynesian Framework. Princeton University Press, Princeton, New Jersey.

Gilchrist, S., Sim, J., Zakrajsek, E., 2010. Uncertainty, financial frictions and investment dynamics. mimeo.

Golosov, M., Lucas, R. E., 2007. Menu costs and phillips curves. Journal of Political Economy 115 (2), 171–199.

Guiso, L., Parigi, G., 1999. Investment and demand uncertainty. The Quarterly Journal of Economics 114 (1), 185–227.

Klenow, P., Kryvtsov, O., 2008. State-dependent or time-dependent pricing: Does it matter for recent u.s. inflation? The Quarterly Journal of Economics 123 (3), 863–904.

Kohlhas, A. N., 2012. Us monetary policy & uncertainty: Testing brainard's hypothesis, mimeo.

Leahy, J., Whited, T., 1996. The effect of uncertainty on investment: Some stylized facts. Journal of Money, Credit and Banking 28 (1), 64–83.

Lein, S. M., 2010. When do firms adjust prices? evidence from micro panel data. Journal of Monetary Economics 57, 696–715.

Narita, F., 2011. Hidden actions, risk-taking and uncertainty shocks, mimeo. University of Minnesota.

Panousi, V., Papanikolaou, D., 2012. Investment, idiosyncratic risk and ownership. Journal of Finance 67 (3), 1113–1148.

Schenkelberg, H., forthcoming. Why are prices sticky? evidence form business survey data. German Economic Review.

Smets, F., Wouters, R., 2007. Shocks and Frictions in US Business Cycles: A Bayesian DSGE Approach. American Economic Review 97 (3), 586–606.

Stahl, H., 2010. Price adjustment in german manufacturing: Evidence from two merged surveys. Managerial and Decision Economics 31 (2-3), 67–92.

Vavra, J., 2013. Inflation dynamics and time-varying uncertainty: New evidence and an ss interpretation, mimeo.

A Link between $FEDISP_t^{qual}$ and $MEANABSFE_{i,t}^{qual}$

Table 11: Time Series Correlation Coefficients between $FEDISP_t$ and $MEANABSFE_{i,t}$

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

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

B Description of the Input Cost Variable

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

To check our procedure we calculate a different proxy for input costs based on producer prices, $\text{Costs}^{ppi}_{k,t}$, which the German Federal Statistical Office publishes for all sectors, but consistently only since 1995. We proceed analogously as above. We compute the quarterly inflation rates of the producer prices for each sector k. We combine the weights of input goods form sector l in the production process in sector k with the respective producer prices inflation rate from sector l. We get a time series of input costs for each sector k for each time period. Time series correlation coefficients between $\text{Costs}_{k,t}$ and $\text{Costs}^{ppi}_{k,t}$ are shown in Table 12. In almost all sectors we find high correlations which lends credence to the use of $\text{Costs}_{k,t}$ since producer prices at sectoral level are not fully available before 1995.

Table 12: Time Series Correlation Coefficients of Input Costs for Each Sector

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

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

C Additional Baseline Regression Output

Table 13: Supplementary Results for Pooled Logit Model for Price Change

Dependent variable: Price change				
	(5)	(6)	(7)	(8)
log(Firmsize)	-0.012***	-0.013***	-0.004***	-0.001
	(0.002)	(0.002)	(0.001)	(0.004)
Tech. capacity^{+}	0.014***		0.010***	
	(0.004)		(0.004)	
Tech. capacity^{-}	0.050***		0.033***	
	(0.006)		(0.006)	
Expempl^{+}	0.030***		0.020***	
	(0.006)		(0.006)	
Expempl^{-}	0.037***		0.025***	
	(0.004)		(0.004)	
Observations	195,605	54,674	167,918	6,208
Pseudo R-squared	0.134	0.138	0.146	0.208

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

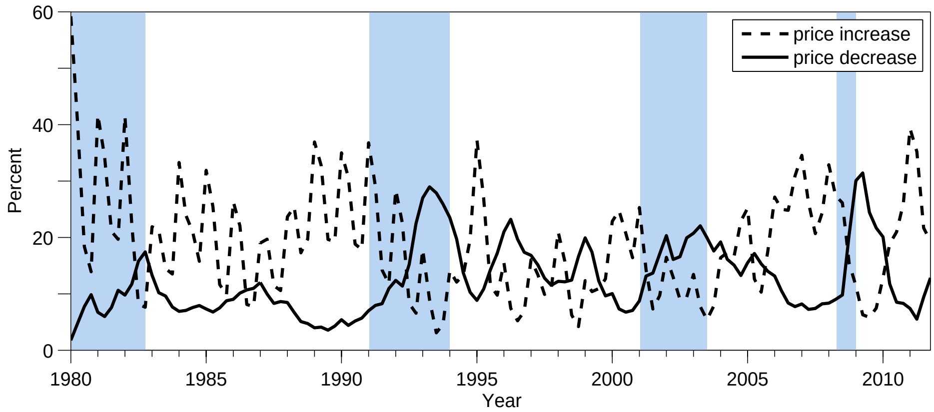
Notes: The table presents marginal effects for a choice of firm-specific variables. Robust and clustered (by firm) standard errors are in parentheses. Included in the pooled logit model but not shown in the table are time fixed effects for each quarter, sector-specific dummies, seasonal dummies and Taylor dummies. Models (5)-(8) include, in addition, all firm-specific variables described in table 6, however marginal effects are presented here only for a selection.

D Asymmetric Price Response

Higher uncertainty increases the probability of price adjustments. We are now interested to see whether this is reflected in higher probabilities of both price increases and decreases. The two price variables are calculated in the following way. If firm i states at date t that it increased (decreased) its price in at least one of the previous three months the dependent variable $Price\ increase_{i,t}$ ($Price\ decrease_{i,t}$) takes the value one, and zero otherwise.[22]

Figure 4 shows the frequency of price increases (dashed line) and price decreases (solid line). The seasonality of price increases is apparent, they mainly take place in the first quarter of the year. This is in line with the findings of Lein (2010). In addition, there are less price increases during recessions, on average. In contrast, the frequency of price decreases rises during recessions; the frequency goes up by about 10 to 20 percentage points.

Figure 4: Frequency of Price Increases and Decreases



Notes: The figure presents the frequency of price increases and price decreases. All data is on a quarterly basis. Shaded regions show recessions as dated by the Economic Cycle Research Institute (ECRI): I/1980 - IV/1982, I/1991 - II/1994, I/2001 - III/2003 and II/2008 - I/2009.

Now we analyze whether a higher uncertainty is reflected in higher probabilities of observing price increases and price decreases. To do so, we estimate quarterly logit models in the spirit of the estimations in the main part of the paper with the respective price increase and price decrease variables as dependent variable. The results are presented in Tables 14 and 15. Heightened uncertainty increases significantly the probability of both price increases as well as price decreases. We, therefore, find that the volatility effect dominates the wait-and-see effect at the firm level. That is, individual prices are more dispersed in times of higher uncertainty.

[22]We discard quarterly observations of $Priceup_{i,t}$ and $Pricedown_{i,t}$ if we observe both a price increase and decrease in the three months period. This is a conservative approach as the net effect for the price is not clear whenever both a qualitative price increase and a qualitative price decrease by a firm are observed within a quarter.

Table 14: Benchmark Results (Pooled Logit Model) with Price Increase

Dependent variable: Price increase								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$ABSFE^{qual}$	0.006***				0.008***			
	(0.002)				(0.002)			
$ABSFE^{quan}$		0.013				0.027		
		(0.020)				(0.028)		
$STDFE^{qual}$			0.015***				0.015***	
			(0.004)				(0.004)	
$STDFE^{quan}$				0.300*				0.115
				(0.159)				(0.117)
Δ Costs					0.492***	0.526***	0.371***	0.252**
					(0.037)	(0.055)	(0.038)	(0.099)
$Orders^{+}$					0.085***	0.077***	0.080***	0.068***
					(0.005)	(0.008)	(0.005)	(0.024)
$Orders^{-}$					-0.013***	-0.016**	-0.016***	0.034*
					(0.005)	(0.008)	(0.005)	(0.019)
$Statebus^{+}$					0.066***	0.077***	0.064***	0.073***
					(0.005)	(0.008)	(0.005)	(0.024)
$Statebus^{-}$					-0.069***	-0.057***	-0.061***	-0.040*
					(0.006)	(0.012)	(0.006)	(0.024)
$Expbus^{+}$					0.034***	0.029***	0.029***	0.003
					(0.005)	(0.010)	(0.006)	(0.022)
$Expbus^{-}$					-0.022***	-0.020*	-0.021***	-0.050**
					(0.005)	(0.011)	(0.005)	(0.024)
Capacity utiliz.					0.001***	0.001***	0.001***	-0.000
					(0.000)	(0.000)	(0.000)	(0.001)
Observations	210,843	55,838	183,165	6,411	167,121	48,440	147,107	5,700
Pseudo R-squared	0.119	0.128	0.114	0.155	0.142	0.139	0.136	0.170

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

Notes: The table presents marginal effects for different uncertainty proxies. Robust and clustered (by firm) standard errors are in parentheses. Included in the pooled logit model but not shown in the table are time-fixed effects for each quarter, sector-specific dummies, seasonal dummies and Taylor dummies. Models (5)-(8) include, in addition, all firm-specific variables described in table 6. $ABSFE^{qual}$: qualitative idiosyncratic uncertainty; $ABSFE^{quan}$: quantitative idiosyncratic uncertainty; $STDFE^{qual}$: 5-quarter rolling window standard deviation of a firm's qualitative expectation errors; $STDFE^{quan}$: 5-quarter rolling window standard deviation of a firm's quantitative expectation errors.

Table 15: Benchmark Results (Pooled Logit Model) with Price Decrease

Dependent variable: Price decrease							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$ABSFE^{qual}$	0.017***				0.009***		
	(0.002)				(0.002)		
$ABSFE^{quan}$		0.229***				0.131***	
		(0.044)				(0.042)	
$STDFE^{qual}$			0.047***				0.025***
			(0.006)				(0.005)
$STDFE^{quan}$				-0.441			
				(0.488)			
Δ Costs					-0.449***	-0.551***	-0.303***
					(0.060)	(0.097)	(0.061)
$Orders^{+}$					-0.007	-0.029**	-0.014**
					(0.008)	(0.015)	(0.006)
$Orders^{-}$					0.137***	0.148***	0.083***
					(0.009)	(0.012)	(0.012)
$Statebus^{+}$					-0.083***	-0.083***	-0.048***
					(0.011)	(0.017)	(0.009)
$Statebus^{-}$					0.104***	0.146***	0.067***
					(0.009)	(0.014)	(0.011)
$Expbus^{+}$					-0.020***	-0.034**	-0.019***
					(0.007)	(0.016)	(0.006)
$Expbus^{-}$					0.114***	0.113***	0.078***
					(0.009)	(0.014)	(0.012)
Capacity utiliz.					-0.000	0.001	0.000
					(0.000)	(0.001)	(0.000)
Observations	120,126	28,107	102,302	3,104	95,360	24,947	82,203
Pseudo R-squared	0.118	0.113	0.137	0.243	0.182	0.153	0.194

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

Notes: The table presents marginal effects for different uncertainty proxies. Robust and clustered (by firm) standard errors are in parentheses. Included in the pooled logit model but not shown in the table are time-fixed effects for each quarter, sector-specific dummies, seasonal dummies and Taylor dummies. Models (5)-(7) include, in addition, all firm-specific variables described in table 6. $ABSFE^{qual}$: qualitative idiosyncratic uncertainty; $ABSFE^{quan}$: quantitative idiosyncratic uncertainty; $STDFE^{qual}$: 5-quarter rolling window standard deviation of a firm's qualitative expectation errors; $STDFE^{quan}$: 5-quarter rolling window standard deviation of a firm's quantitative expectation errors. Model (8) is not estimated due to the low number of observations.