Essays on Uncertainty and Business Cycles

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Christian Grimme

Referent: Prof. Dr. Kai Carstensen
Korreferent: Prof. Rüdiger Bachmann, Ph.D.
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Introduction

The Great Recession led to large and persistent drops in real output. At the same time many proxies for uncertainty jumped up.[1] Policymakers believe that uncertainty was an important factor explaining the dynamics during the recession of 08/09 and in the Eurozone crisis. For example, in 2009, the Chief Economist of the International Monetary Fund (IMF) Olivier Blanchard wrote that uncertainty "affects consumption and investment decisions, and is largely behind the dramatic collapse in demand" (see Blanchard, 2009). In 2014, Mario Draghi, President of the European Central Bank (ECB), noted that uncertainty "is weighing on business investment and slowing the rate at which workers are being rehired" (see Draghi, 2014). These claims raise two main questions. First, how do we measure uncertainty, a variable that is not directly observable? Second, how are increases in uncertainty transmitted to the economy?

The present work contributes to the literature on uncertainty by using empirical methods to measure uncertainty and volatility, and empirical and theoretical methods to analyze two transmission channels through which uncertainty is linked to the business cycle. The first chapter looks into the problem of measuring inflation uncertainty and proposes to use common information contained in a variety of different uncertainty proxies. In the second chapter, we develop measures of firm-specific volatility and quantify the effect of heightened volatility on the price setting behavior of firms and analyze whether this link

[1] See, e.g., Bachmann, Elstner, and Sims (2013), Baker, Bloom, and Davis (2013), Born, Breuer, and Elstner (2014), Bloom (2009), Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2012), Henzel and Rengel (2014), Jurado, Ludvigson, and Ng (2015).

changes the effectiveness of monetary policy. The third chapter compares the effects of heightened idiosyncratic uncertainty on credit spreads in bank-based and market-based financial systems.

Chapter 1.[2] The first chapter deals with the problem of measuring inflation uncertainty. Any individual proxy for inflation uncertainty relies on specific assumptions that are most likely not fulfilled completely. Therefore, proxies most likely suffer from idiosyncratic measurement errors. To reduce these problems, we use a principal component analysis to extract common information contained in different measures. To this end, we rely on the most commonly used proxies for inflation uncertainty. These include survey disagreement and the realized forecast error variance derived from a panel of professional forecasters and proxies derived from model-based approaches such as GARCH and stochastic volatility. In addition, we present several measures derived from a large number of forecast models.

We show that the first principal component provides an adequate indicator of inflation uncertainty because it condenses the information common to all measures and, therefore, overcomes the problem of idiosyncratic measurement errors. Notably, each individual measure contributes to the indicator with a similar weight. The common component remains virtually unaffected if we exclude one of the measures. Furthermore, analyzing the part of the dynamics that is not captured by the first principal component, we are able to see to which extent the individual measures deliver contradictory signals. We find that some caution is warranted with disagreement measures derived from survey data and forecast models, because the idiosyncratic parts of these measures tend to move in opposite directions over the business cycle. Using only one individual disagreement measure, therefore, may be misleading particularly during turbulent times.

Central banks are regularly confronted with demands to increase the inflation target. Keeping in mind that inflation uncertainty comes with costs that go beyond the costs of inflation (for example, nominal contracts become riskier), we use our indicator to analyze the link between inflation uncertainty and inflation. Our results support the Friedman-Ball hypothesis – higher inflation rates lead to higher inflation uncertainty. This suggests that raising inflation would imply additional costs, which are related to the increase in inflation uncertainty, that

[2] This chapter is based on the paper "Inflation Uncertainty Revisited: A proposal for robust measurement", jointly written with Steffen Henzel and Elisabeth Wieland. The paper is published in *Empirical Economics* (Grimme, Henzel, and Wieland, 2014).

need to be considered. By contrast, using the individual uncertainty proxies one at a time reveals contradictory results with respect to the Friedman-Ball hypothesis. Therefore, the measurement errors in the individual proxies do have an influence on the dynamics of the uncertainty measures following a sudden increase in inflation.

CHAPTER 2.[3] This chapter analyzes whether idiosyncratic volatility affects the price setting of firms and thus the transmission of monetary policy into the real economy. One reason why monetary policy has an effect on real variables in the short run is that prices are sticky. If heightened volatility changes the degree of price stickiness, this would affect the effectiveness of monetary policy.

We follow two strategies to construct firm-level volatility measures from the IFO Business Climate Survey. Based on qualitative survey questions, we construct expectation errors at the firm level and take the absolute value of these errors as a proxy for idiosyncratic volatility. For a subset of firm responses we construct a quantitative volatility measure. The second strategy relies on the same qualitative and quantitative expectation errors but uses a firm-specific rolling window standard deviation. All four measures are highly correlated.

From the IFO Business Climate Survey we also have information on the price setting at the firm level. This enables us to estimate a probit model in which we asses to what extent an increase in firm-specific volatility affects the frequency of price adjustment. We find that heightened volatility increases the frequency of price changes, however the effect is rather moderate. The tripling of volatility during the recession of 08/09 leads to an increase in the quarterly likelihood of a price change from 31.6% to 32.3%.

What do the effects we find at the micro-level imply for the effectiveness of monetary policy? To answer this question we use a standard New Keynesian dynamic stochastic general equilibrium (DSGE) model with Calvo-type price setting. The empirical exercise gives us an elasticity for the probability of a price change with respect to an increase in firm-level volatility. We use this elasticity to calibrate a change in the Calvo parameter in the DSGE model to capture a change in idiosyncratic volatility. We find that during a time in which volatility triples a 25 basis point cut in the nominal interest rate would have lost about 1.6% of its effect on real output on impact. In the 08/09 recession we observe

[3] The chapter is based on the CEPR Discussion Paper "Time-Varying Business Volatility, Price Setting, and the Real Effects of Monetary Policy", jointly written with Rüdiger Bachmann, Benjamin Born and Steffen Elstner (Bachmann, Born, Elstner, and Grimme, 2013).

an overall increase in the share of firms adjusting prices by about 7 percentage points. This number implies that after a monetary stimulus of 25 basis points the total loss in effectiveness amounts to almost 17%. Therefore, changes in price flexibility are potentially an important driver for the effectiveness of monetary policy, however, we find that firm-level volatility does not contribute much to these price changes.

CHAPTER 3. This chapter takes an empirical and theoretical look at the relationship between idiosyncratic uncertainty and credit spreads. It analyzes whether credit spreads behave differently in bank-based and market-based financial systems following an uncertainty shock. An increase in uncertainty about idiosyncratic productivity increases the probability of firm default and lenders demand a higher risk premium from borrowers. We analyze whether banks act differently than the capital market in times of heightened uncertainty. In contrast to the capital market, banks are able to form long-term relationships with borrowers, through these relationships banks get to know borrowers better and acquire additional information. To preserve these relationships, banks smooth loan rates over the business cycle to protect firms from fluctuations in market rates (Berger and Udell, 1992).

Empirically, the contribution of the paper is to analyze whether credit spreads on corporate bonds behave differently in response to uncertainty shocks than credit spreads on bank loans. We follow Bachmann, Elstner, and Sims (2013) and use survey data from the Philadelphia Fed's Business Outlook Survey and the IFO Business Climate Survey to construct idiosyncratic uncertainty measures for the United States and Germany, respectively. For each country we calculate two credit spreads. The market spread is computed as the difference between corporate bond yields and government bond yields, the bank spread is the difference between bank loan rates and government bond yields. Vector autoregressions show that after a surprise increase in uncertainty, market spreads increase more than bank spreads. This is due to the fact that corporate bond yields increase while bank loan rates decrease. Therefore, economies, which are characterized by firms relying mainly on financial markets for external finance, like the United States, are confronted with relatively higher external financing costs than bank-based financial systems, like Germany, in times of heightened uncertainty.

The theoretical part of the chapter has two contributions. First, we check whether a DSGE model with a costly state verification problem produces increasing or decreasing lending rates in response to an uncertainty shock. This type of model is used by many papers in the literature on uncertainty and financial frictions (see, e.g., Christiano, Motto, and Rostagno, 2014). Employing two different calibration strategies, one solely for Germany, the other encompassing a wide range of values for each parameter, we find that the model predicts increasing lending rates. Following an uncertainty shock, default risk increases, which leads to a higher risk premium. Therefore, this model supports the response of capital markets to heightened uncertainty.

Second, we formulate a stylized partial equilibrium model with costly state verification that contains the possibility to form bank-borrower relationships. Having formed a lending relationship, the bank faces lower information asymmetries. If the reduction in these asymmetries is sufficiently large, the relationship bank has an incentive to offer relatively low lending rates in times of high uncertainty. A low lending rate counteracts the increase in the probability of firm default, which makes it more likely that, after uncertainty vanished, the bank can exploit the fact that it has more information about the borrower than other lenders and demand comparatively high loan rates.

In sum, we conclude in this chapter that the effects of uncertainty shocks on the cost of external finance are dampened to some extent by the banking system. Therefore, if credit costs for firms do not increase much, uncertainty transmitted through the credit cost channel might be less of a concern for the conduct of monetary policy in bank-based financial systems.

CHAPTER 1

Inflation Uncertainty Revisited: A Proposal for Robust Measurement

Any measure of unobserved inflation uncertainty relies on specific assumptions which are most likely not fulfilled completely. This calls into question whether an individual measure delivers a reliable signal. To reduce idiosyncratic measurement error, we propose using common information contained in different measures derived from survey data, a variety of forecast models, and volatility models. We show that all measures are driven by a common component, which constitutes an indicator for inflation uncertainty. Moreover, our results suggest that using only one individual disagreement measure may be misleading particularly during turbulent times. Finally, we study the Friedman-Ball hypothesis. Using the indicator, we show that higher inflation is followed by higher uncertainty. In contrast, we obtain contradictory results for the individual measures. We also document that, after an inflationary shock, uncertainty decreases in the first two months which is traceable to the energy component in CPI inflation.

1.1 Introduction

In the follow-up of the seminal speech of Friedman (1977), a still ongoing debate has originated concerning the link between inflation and inflation uncertainty (Ball, 1992, Cukierman and Meltzer, 1986). Empirical testing of the causes and consequences of increased inflation uncertainty necessitates a valid measure. Given that inflation uncertainty is an unobserved variable, many different measures have been proposed in the literature. While some studies rely on survey-based measures, others depend on volatility derived from time series models, or use realized forecast errors. Each measure is derived from different assumptions which are most likely not fulfilled completely. This calls into question whether an individual measure delivers a reliable signal at any time. That is, any individual measure most likely suffers from idiosyncratic measurement error. Hence, empirical results concerning the relationship between inflation uncertainty and inflation depend crucially on the choice of the uncertainty measure.[4]

In this study, we propose an approach to mitigate the idiosyncratic measurement error problem. To this end, we derive the most commonly used measures of inflation uncertainty. These include survey disagreement derived from a panel of forecasters, realized forecast error variance, and model-based approaches such as GARCH and stochastic volatility. Moreover, we present an approach which relies on a variety of forecast models. We use these measures to construct an indicator of inflation uncertainty that condenses the information contained in all measures and overcomes the idiosyncratic measurement error problem.

We demonstrate that all measures are driven by a common component, which we interpret as an indicator for inflation uncertainty. Notably, each individual measure contributes to the indicator with a similar weight. The common component thus remains virtually unaffected when we discard one of the measures. Moreover, we document that individual measures have the tendency to drift apart when uncertainty rises. That is, the measurement error problem seems to be larger during "uncertain times". Accordingly, using individual measures to examine the relation between these two variables yields ambiguous results. Such a finding emphasizes the benefits of the indicator approach.

Furthermore, the indicator approach helps us analyze to which extent individual measures may deliver a misleading signal since it enables us to analyze

[4] Mixed results with respect to the direction of causality are obtained *inter alia* by Grier and Perry (1998, 2000), Grier, Henry, Olekalns, and Shields (2004), and Berument and Dincer (2005). See also Davis and Kanago (2000) and Fountas and Karanasos (2007) and the papers cited therein.

the part of the dynamics which is not captured by the common component. In particular, we discuss whether disagreement is a good proxy for uncertainty.[5] For this purpose, we analyze disagreement in survey forecasts and disagreement derived from a variety of forecast models. It appears that both disagreement measures co-move with the other uncertainty measures and are to a large extent reflected in the common component. However, some caution is warranted because our results also suggest that using only one individual disagreement measure may be misleading particularly during turbulent times.

In a further step, we take advantage of our approach and study the relationship between inflation and inflation uncertainty. This topic has recently regained relevance because several economists call for a temporary increase of central banks' inflation target to mitigate the problem of debt overhang and to fight unemployment.[6] Against this background, the Friedman-Ball hypothesis suggests that high inflation rates may lead to increased inflation uncertainty which brings about economic cost (see, for instance, Bernanke and Mishkin, 1997). Our results are in favor of the Friedman-Ball hypothesis. We also document that, after an inflationary shock, uncertainty decreases during the first two months. Such a behavior appears to be traceable to the energy component in the CPI since we do not observe a decrease following a shock to core inflation. After a few months, uncertainty increases swiftly for all inflation-related shocks.

A few studies compare different approaches to measure inflation uncertainty. For instance, Batchelor and Dua (1993, 1996) contrast inflation uncertainty obtained from subjective probability distributions from the U.S. Survey of Professional Forecasters (SPF) with different model-based measures. They find no significant correlation between both categories. Taking uncertainty measures derived from the SPF as a benchmark, Giordani and Söderlind (2003) document that model-based measures in general have problems in timely capturing regime changes. Nonetheless, the standard deviation of a VAR estimated on a rolling window tracks the time profile of SPF uncertainty quite well. Chua,

[5] The relation between disagreement and uncertainty is the subject of an ongoing debate. Bomberger and Frazer (1981), Bomberger (1996, 1999) and Giordani and Söderlind (2003) find supportive results, yet other studies report only a weak relationship or reject disagreement as a proxy (Zarnowitz and Lambros, 1987, Lahiri, Teigland, and Zaporowski, 1988, Rich and Butler, 1998, Döpke and Fritsche, 2006, Rich and Tracy, 2010). Lahiri and Sheng (2010b) argue that disagreement is a reliable proxy for overall uncertainty if the forecast environment is stable.

[6] See, for instance, the IMF Staff Position Note by Olivier Blanchard et al. (SPN/10/03), the comment by Ken Rogoff in the Financial Times on Aug 8, 2011, the address by Charles L. Evans at the Outlook Luncheon on Dec 5, 2011, and the comment by Paul Krugman in the NY Times on April 6, 2012.

Kim, and Suardi (2011) identify a particular GARCH model that matches the SPF measure closest.

All of the above studies take subjective densities of the SPF as the observational equivalent of inflation uncertainty. Although SPF is conducted on a quarterly frequency, a time path for subjective uncertainty relating to forecasts with a constant forecast horizon is available only on an annual basis. However, uncertainty may emerge rather quickly. Against this background, recent studies analyze the effects of uncertainty at a monthly frequency (Bloom, 2009, Knotek and Khan, 2011, Bachmann, Elstner, and Sims, 2013). To address this issue, our measure of inflation uncertainty is derived on a monthly basis, yet we document that our uncertainty indicator produces a time profile which is similar to yearly SPF uncertainty.

The remainder of the paper is organized as follows. In Section 1.2, we introduce survey-based measures as well as model-based measures. Moreover, we present a "forecast-based" approach which relies on multiple forecast models. The relation between the different measures is analyzed in Section 1.3. In Section 1.4, we investigate the link between inflation and inflation uncertainty. Section 1.5 concludes.

1.2 Individual Measures of Inflation Uncertainty

1.2.1 Survey-Based Measures

First, we derive uncertainty measures from survey data. We use individual forecasts for CPI inflation from professional forecasters conducted by Consensus Economics (CE). CE reports average annual growth rates of expected inflation for the current and next calendar year. However, since the forecast horizon varies for each month, the cross-sectional dispersion of forecasts is strongly seasonal and converges towards zero at the end of each year (Lahiri and Sheng, 2010a). To obtain twelve-months-ahead inflation forecasts, we follow Dovern, Fritsche, and Slacalek (2012) and calculate a weighted moving average of the annual forecasts. For each month m, the fixed horizon forecast is obtained by weighting the two available point estimates according to their respective share in the forecast horizon; i.e., $\frac{12-m+1}{12}$ for the current year's forecast and $\frac{m-1}{12}$ for the next year's forecast. The sample period covers the period 1990:M1 to 2009:M12. The average number of fixed horizon forecasts ranges between 16 and 32 per period, with a mean value of 25 observations.

The CE survey is advantageous because it polls professional forecasters who should be well informed about the current state of the economy. Moreover, individual data is provided and the names of the forecasters are given alongside the numbers. Hence, there is a strong incentive to make a well-founded prediction in order not to damage the forecaster's reputation. Against this background, Dovern and Weisser (2011) find that individual forecasts of U.S. inflation are largely unbiased. Moreover, CE data has the advantage that it runs on a monthly frequency. As uncertainty may move abruptly, many of the effects we want to measure would be harder to identify in low frequency data.

Among others, Bomberger and Frazer (1981), Cukierman and Wachtel (1982), and Batchelor and Dua (1993, 1996) suggest using the root mean squared error ($rmse^s$) as a measure of uncertainty. It is calculated by averaging the individual squared forecast errors in each period t:

$$rmse_t^s = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(\pi_{t+12} - \pi_{i,t}^e\right)^2} \tag{1.1}$$

where π_{t+12} denotes realized 12-month ahead CPI inflation and $\pi_{i,t}^e$ is the individual point forecast from CE made at time t. As far as the timing is concerned, we follow Batchelor and Dua (1993, 1996). This implies that $rmse^s$ is an ex-post measure (see also Hartmann and Herwartz, 2014). That is, a forecast error realized at time $t+12$ represents uncertainty at time t.

Bomberger and Frazer (1981), Bomberger (1996, 1999), and Giordani and Söderlind (2003) propose the cross-sectional dispersion of point forecasts (disagreement) as a measure of uncertainty. Instead of using the cross-sectional standard deviation of forecasts, we follow Mankiw, Reis, and Wolfers (2003) and rely on the interquartile range (iqr^s) since it is more robust to outliers. iqr^s is defined as the difference between the 75$^{\text{th}}$ and the 25$^{\text{th}}$ percentiles.[7]

Mankiw, Reis, and Wolfers (2003) point out that the distribution of forecasts may become multimodal if model uncertainty is high. This is the case, for

[7] We also computed the standard deviation and the quasi-standard deviation of forecasts (Giordani and Söderlind, 2003). The quasi-standard deviation is defined as half the difference between the 84th and 16th percentiles. With normally distributed data, this measure equals the standard deviation. The correlation coefficient of these alternative dispersion measures and iqr^s amounts to 0.86 and 0.90, respectively.

instance, around structural breaks. As dispersion neglects the form of the distribution Rich and Tracy (2010), among others, suggest using a histogram-based entropy (ent^s) which is computed as:

$$ent_t^s = -\Big(\sum_{k=1}^{n} p(k)_t[ln(p(k)_t)]\Big) \tag{1.2}$$

where $p(k)$ denotes the relative frequency of individual forecasts falling in a certain interval k. For a given number of bins and a constant bin width, the histogram-based entropy is maximized if the forecasts are distributed equally among all bins. The entropy provides additional information beyond iqr^s. Given the cross-sectional standard deviation of forecasts, the entropy changes with the shape of the histogram of forecasts. In particular, the normal distribution exhibits a higher entropy than any other distribution of the same variance (Vasicek, 1976).

1.2.2 Forecast-Based Measures

As a complement to the survey-based measures, we propose a forecast-based approach which relies on multiple forecast models. To simplify the analysis, we use VAR models, which are a popular forecast device because of their ability to generate multi-step predictions. A VAR model is also employed by Giordani and Söderlind (2003). To obtain a time-varying uncertainty measure, they recursively estimate a single VAR model and calculate a standard deviation of the forecast error of inflation for each period. Chua, Kim, and Suardi (2011) follow this idea by deriving error bands from the recursive bootstrapped VAR approach proposed by Peng and Yang (2008). However, this approach comes at the cost of being conditional on a specific forecast model which is assumed to provide the correct description of the data. Moreover, the model is assumed to be the same for all forecasters. Hence, model uncertainty is virtually absent and forecaster diversity is neglected. Finally, uncertainty is derived from VAR residuals which are assumed to be homoskedastic. In effect, this is not consistent with the notion that uncertainty changes systematically over time. To overcome these possible drawbacks, we do not use VAR residuals but point forecasts of a variety of VAR models.

To obtain multiple forecast models, we select a number of activity variables proposed by Stock and Watson (1999) to forecast U.S. inflation. The authors identify different subgroups of variables. To keep the analysis tractable, we choose one representative from each of these subgroups. We end up with 15 variables, which are described in Table 1.5 in the appendix. To derive twelve-months-ahead forecasts for inflation, we build a number of different VAR models. Each VAR model is limited in size to avoid over-fitting problems (for a detailed discussion see, for instance, Berg and Henzel (forthcoming), and Henzel and Mayr (2013)). It comprises the target variable and up to four additional activity variables. Finally, we construct all VAR models that fulfill this criterion; i.e., we consider all possibilities to choose up to four variables out of the 15 activity variables. The lag length of each VAR model is determined by BIC, and we end up with a total number of 1.941 different inflation forecasts for each month. The estimation is based on a rolling window covering 20 years of data.[8] That is, the first sample comprises observations beginning in 1970:M1 and ending in 1990:M1. Subsequently, we derive one-year-ahead forecasts for inflation. We iterate through time until 2009:M12. Note that the estimation period contains the disinflation period during the 1980s. Hence, inflation enters the VAR model in first differences (Stock and Watson, 1999, 2007). Calculating RMSE as defined in equation (1.1) yields a forecast-based measure of inflation uncertainty ($rmse^f$). Forecast-based disagreement (iqr^f) is given by the dispersion among the point forecasts measured by the interquartile range. According to equation (1.2), we also calculate an entropy-based measure (ent^f).

1.2.3 Model-Based Measures

Conditional Forecast Error Variance

ARCH models of many different shapes have been extensively used to model inflation uncertainty in the U.S.[9] A number of studies highlight the presence of structural breaks in the inflation process.[10] To account for such events like changes in the monetary regime or the level of steady-state inflation, we follow these studies and opt for a GARCH model with time-varying parameters. The

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[8] Giordani and Söderlind (2003) advocate the use of a "windowed" VAR â€" in opposition to a recursive VAR – where changes in the inflation process are quickly reflected in the parameter estimates.

[9] See, for instance, Engle (1983), Cosimano and Jansen (1988), Brunner and Hess (1993), Grier and Perry (1996), Grier and Perry (2000), Elder (2004), Grier, Henry, Olekalns, and Shields (2004) and Chang and He (2010).

[10] See, for instance, Evans (1991), Evans and Wachtel (1993), Bhar and Hamori (2004), Berument, Kilinc, and Ozlale (2005), Caporale and Kontonikas (2009), and Caporale, Onorante, and Paesani (2012).

model is given by a signal equation (1.3), a state equation (1.4) and equation (1.5) describing how conditional error variance evolves.

$$\pi_t = [1\ \pi_{t-1}\ \pi_{t-2}]\ \alpha_t + e_t \qquad e_t \sim N(0, h_t) \tag{1.3}$$
$$\alpha_{t+1} = \alpha_t + \eta_t \qquad \eta_t \sim N(0, Q) \tag{1.4}$$
$$h_t = d + \phi e_{t-1}^2 + \gamma h_{t-1} \tag{1.5}$$

Here, α_t is a vector of time-varying coefficients which follow a random walk. We model inflation as an AR(2) process which meets the needs to reproduce the cyclical behavior. h_t describes conditional error variance which emerges from a GARCH(1,1) process. Q is a homoskedastic covariance matrix of shocks η_t. The estimation is based on a rolling window covering 20 years of monthly data to replicate a forecast situation. In accordance with the forecast-based measures introduced in the previous section, the first estimation window starts in 1970:M1 and ends in 1990:M1. The Kalman filter provides an estimate for the variance of the forecast error in the last period. Note that this variance combines model uncertainty emerging from time-variation of the coefficients and uncertainty emerging from the shock process η_t (see Evans, 1991, Caporale, Onorante, and Paesani, 2012, for a detailed explanation). We successively iterate through time until 2009:M12 and obtain an estimate for the variance of the forecast error at each point in time which obtains the label *garch*.

Stochastic volatility

Stochastic volatility models are used in financial econometrics to model error variance as a latent stochastic process (see, among others, Harvey, Ruiz, and Shephard, 1994, Kim, Shephard, and Chib, 1998). Moreover, a stochastic volatility model is proposed as a forecast model for U.S. inflation by Stock and Watson (2007). The variance of first moment shocks is assumed to be driven by an exogenous stochastic process. This is in contrast to ARCH models where error variance is fully described by its own past. We follow Dovern, Fritsche, and Slacalek (2012) and employ the model to measure inflation uncertainty. The state-space representation is given by equations (1.6) to (1.10).

$$\pi_t = \mu_t + e_t \qquad e_t \sim N(0, \sigma^2_{e,t}) \tag{1.6}$$
$$\mu_{t+1} = \mu_t + \eta_t \qquad \eta_t \sim N(0, \sigma^2_{\eta,t}) \tag{1.7}$$
$$\log \sigma^2_{e,t+1} = \log \sigma^2_{e,t} + \nu_{1,t} \tag{1.8}$$
$$\log \sigma^2_{\eta,t+1} = \log \sigma^2_{\eta,t} + \nu_{2,t} \tag{1.9}$$
$$\begin{pmatrix} \nu_{1,t} \\ \nu_{2,t} \end{pmatrix} \sim N(0, \gamma I_2) \tag{1.10}$$

Here, e_t is a short-term shock in the measurement equation (1.6) with variance $\sigma^2_{e,t}$. Moreover, the permanent component of inflation μ_t follows a random walk which is driven by a (level) shock η_t with variance $\sigma^2_{\eta,t}$. The model is estimated with the Gibbs sampler. As in the case of *garch*, we use a rolling window covering 20 years of data. Hence, we only use information known to the researcher at the time the estimate is provided. Finally, we follow the arguments of Ball and Cecchetti (1990) and use the square root of the variance of permanent shocks $\sigma^2_{\eta,t}$ as the measure of inflation uncertainty. Subsequently, it is denoted by *ucsv*.

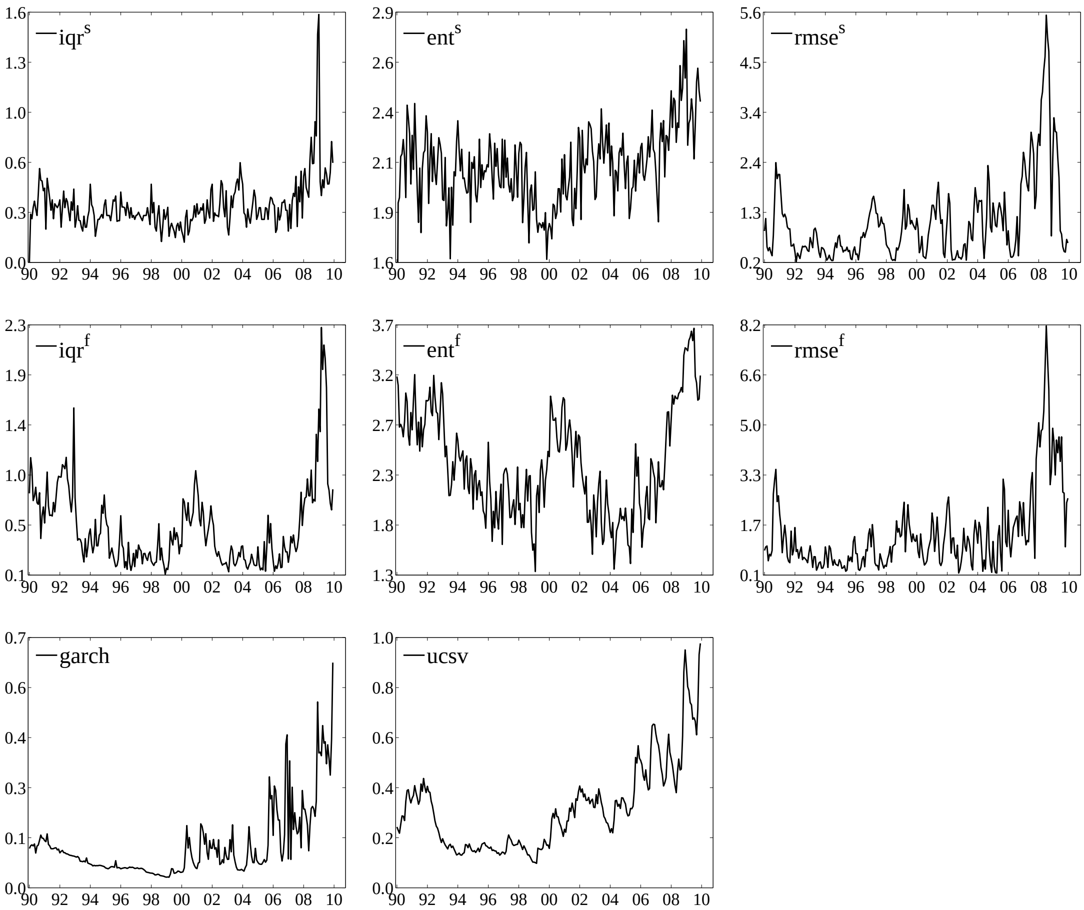
1.3 Characteristics of Uncertainty Measures

1.3.1 Descriptive Analysis

All measures presented in Section 1.2 require a number of assumptions to work as good proxies for uncertainty. Most likely, these assumptions are not fulfilled completely. For instance, deriving valid measures from survey-based approaches assumes that the survey is conducted such that bias and measurement error is small. Moreover, disagreement and entropy are valid proxies only if there is a positive correlation between the dispersion of forecasts of respondents and uncertainty of the participants. However, it might be the case that individual forecasters are highly uncertain and, therefore, reluctant to deviate from the other forecasters. *rmse* is an ex-post measure that captures realized forecast error variance, and we assume that this differs from the subjective uncertainty of the forecaster only by a random error. Measures inferred from the forecast-based approach work as indicators for uncertainty if linear time series models are a good approximation of the model used by individual forecasters. Finally, model-based measures are conditional on a specific forecast model. Moreover, this particular model is assumed to be the same for all forecasters, that is, there is no disagreement.[11] In addition, *garch* provides the conditional variance which is driven by forecast errors from previous periods. Hence, each measure proposed in the literature is probably contaminated by idiosyncratic measurement error. Thus, it should be beneficial to base the analysis on information contained in all measures jointly.

We generate the eight individual uncertainty measures introduced in Section 1.2: three survey-based measures (iqr^s, ent^s, $rmse^s$), three forecast-based measures (iqr^f, ent^f, $rmse^f$), and two model-based measures (*garch*, *ucsv*). The individual measures are depicted in Figure 1.1. All eight measures exhibit a similar pattern, particularly during the recent economic crisis. However, there are also periods when some of the measures diverge.

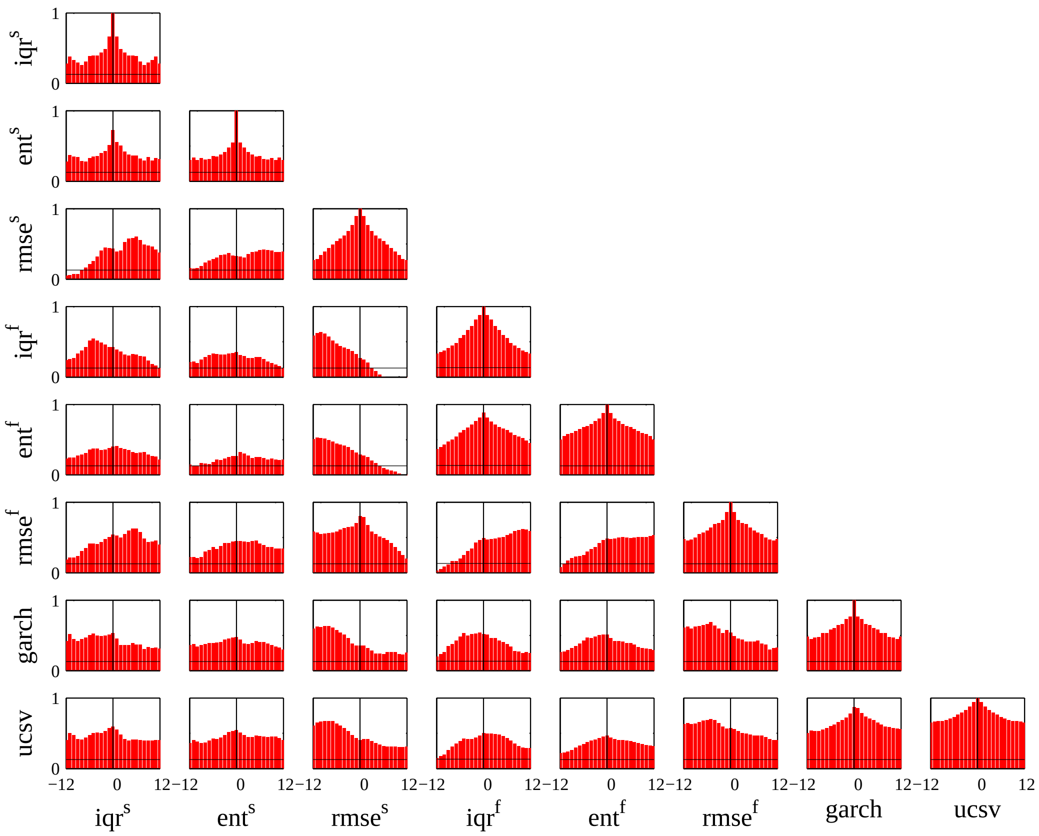
Figure 1.1: Survey-Based (iqr^s, ent^s, $rmse^s$), Forecast-Based (iqr^f, ent^f, $rmse^f$), and Model-Based (*garch*, *ucsv*) Measures of Inflation Uncertainty



[11] According to Lahiri and Sheng (2010b), overall forecast uncertainty is the sum of the variance of future aggregate shocks and the variance of idiosyncratic shocks. Model-based measures capture only the uncertainty common to all fore-casters and neglect forecaster-specific shocks which are responsible for the disagreement among different forecasters.

In the following, we present some descriptive statistics to characterize the individual measures. Figure 1.2 displays the autocorrelation of the eight uncertainty measures on the main diagonal. It shows that the autocorrelation is positive and significant at the 5% level for each measure. The lowest degree of autocorrelation is found for survey disagreement whereas the most sluggish measure is *ucsv*. In general, inflation uncertainty seems to be a persistent phenomenon. Cross-correlations are given on the off-diagonal elements of Figure 1.2. We find that cross-correlations are high and significantly positive among all series and throughout all leads and lags. We take this as a first indication that all measures contain a common component. Also note that $rmse^s$ and $rmse^f$ tend to lead the other measures.

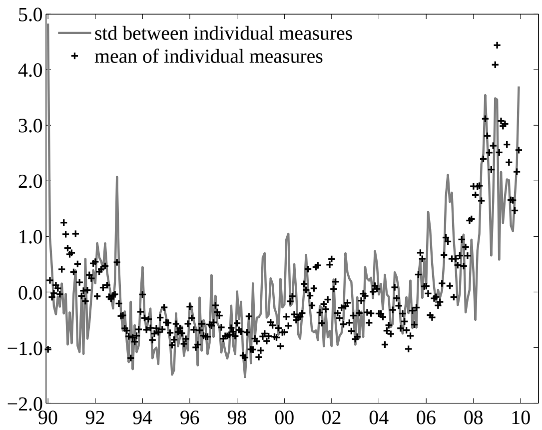
Figure 1.2: Cross-Correlations of Uncertainty Measures



Notes: The bars represent cross-correlations $\mathrm{corr}(y_{i,t}, y_{j,t+k})$ for each pair of variables, where $y_{i,t}$ denotes the row i variable and $y_{j,t+k}$ is given in the column j. k varies between -12 and $+12$. The 5% significance level is indicated by the horizontal line.

The extent of co-movement over time is revealed in Figure 1.3. Here, we depict the evolution of the cross-sectional standard deviation between all measures at each point in time (solid line). We observe that the standard deviation fluctuates around a constant value during the first part of the sample, yet the measures start to diverge towards the end of the sample. The co-movement between all eight measures further decreases during the recent crisis. Figure 1.3 also depicts the cross-sectional mean of all eight measures, which is strongly correlated with the cross-sectional standard deviation; the correlation coefficient amounts to 0.68. Thus, during more turbulent times, individual measures have the tendency to drift apart and measuring uncertainty becomes more challenging. It appears that a method attenuating the idiosyncratic measurement error problem is particularly beneficial in times of high uncertainty.

Figure 1.3: Dispersion of Uncertainty Measures



Notes: Individual uncertainty measures have been standardized before calculating the cross-sectional standard deviation.

1.3.2 Common Characteristics

To eliminate the idiosyncratic components from the data, we can exploit the commonalities among individual measures documented in the previous section. That is, we use the cross-sectional dimension of the data to alleviate the idiosyncratic measurement error problem. For this purpose, we conduct a Principal Component Analysis. As mentioned above, the two variables $rmse^s$ and $rmse^f$ seem to lead the rest of the indicators. We obtain a maximum average cross correlation at 8 and 5 lags, respectively. When estimating the common factors, we follow Stock and Watson (2002) and account for the lead characteristics of these variables. Table 1.1 shows the loading coefficients of the first three principal components and the individual and cumulative variance proportions of those components.

Table 1.1: Principal Component Analysis

	PC 1	PC 2	PC 3	
Eigenvalues	4.98	1.07	0.72	
Variance Proportion	0.62	0.13	0.09	
Cumulative Proportion	0.62	0.76	0.85	
	Loadings			R^2
iqr^s	0.34	0.34	-0.44	0.59
ent^s	0.31	0.44	-0.51	0.48
$rmse^s$	0.36	-0.04	0.31	0.63
iqr^f	0.33	-0.56	-0.23	0.56
ent^f	0.33	-0.57	-0.26	0.54
$rmse^f$	0.37	0.10	0.20	0.70
$garch$	0.38	0.09	0.40	0.72
$ucsv$	0.39	0.17	0.35	0.76

Notes: R^2 calculated from a regression of the respective individual uncertainty measure on PC1.

The first principal component (PC1) accounts for the major part of the dynamics of the data as it explains 62% of the total variation of the underlying series. The second principal component (PC2) carries less information since it explains only 13% of the variation. A scree test indicates that there are two informative principal components in the dataset (the first two eigenvalues are larger than one). Table 1.1 also shows that the contribution of the third principal component is relatively small. We conclude that the bulk of the variation is explained by two principal components and the following analysis thus focuses on these two components.

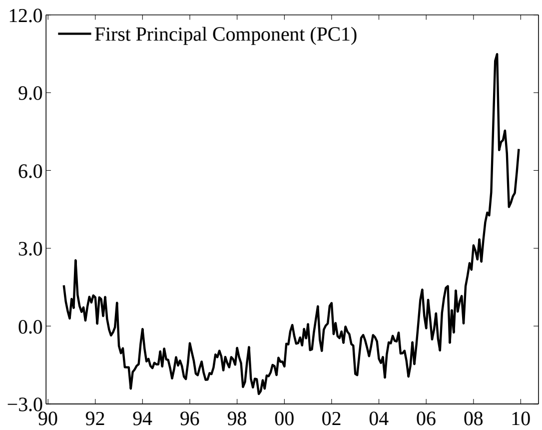
From Table 1.1, we infer that all eight loading coefficients of PC1 are positive and lie between 0.31 and 0.39. That is, the loadings are all similar in magnitude and each of the proposed measures therefore carries information we can use to estimate unobserved inflation uncertainty.[12] This is also reflected by the fact that PC1 has noticeable explanatory power for each of the individual measures. As indicated by the R^2 in Table 1.1, the variance share explained by PC1 varies between 48% and 76%. Also note that PC1 is almost identical to a simple

[12] Note that given the very similar factor loadings, PC1 remains virtually unaffected when we exclude one measure from the analysis. Our results thus do not hinge on one individual measure.

average of the standardized individual measures since the loadings are similar. In applied research, taking a simple average is thus sufficient to extract the common component.[13]

The first principal component is shown in Figure 1.4. Following a rather tranquil period with moderate movements, PC1 starts to rise beginning roughly in 2007 followed by a surge towards the end of 2008, which coincides roughly with the peak of the recent economic crisis. This is in line with, for instance, Clark (2009) who documents that macroeconomic variability has recently been increasing due to larger financial and oil price related shocks. Also note that a large part of the surge in uncertainty is only temporary as PC1 quickly drops to about half the value of the 2008-peak in the subsequent months.[14]

Figure 1.4: Uncertainty Indicator (PC1)



To analyze the information content of PC1, we study the co-movement of PC1 with economic variables that one would expect to be related to inflation uncertainty. Contemporaneous correlations of PC1 and a collection of key variables are presented in Table 1.2. Results show that PC1 is closely linked to the variability of nominal variables such as commodity prices, long-term interest rates, and money. Similarly, variables representing financial market risk (*vix*,

[13] The results in this paper remain unchanged when we replace PC1 with the average of the standardized measures. The results are available upon request.

[14] Due to the CE survey, the main analysis is limited to a sample beginning in 1990. Hence, our sample covers a rather tranquil period as far as inflation is concerned. To see whether the results also hold for periods of high and volatile inflation, we conduct the analysis for the years 1970 to 1995 considering only the forecast-based and model-based approaches. Our results also hold for the earlier time span. First, there appears to be a common component which explains the majority of the variation in the data (58%). Second, all individual measures contribute with a non-negligible weight. Third, the loadings are similar. Detailed results are available upon request.

ted spreads, corporate bond spreads, and squared returns) seem to rise with PC1. Moreover, PC1 appears to be positively linked to the variability of production growth. Finally, all variables representing the business cycle indicate that inflation uncertainty is associated with economic contraction. We also observe a negative association with short-term interest rates which are, in general, pro-cyclical over the business cycle. Notably, the correlation obtained for long-term rates is somewhat lower compared to short-term rates. This is probably due to the fact that the long-term interest rate is partly driven by the inflation risk premium, which tends to increase along with inflation uncertainty.

1.3.3 Group-Specific Characteristics

We now shed some light on the idiosyncratic movements; i.e., the dynamics which are specific to (some of) the individual measures. The informative part of the idiosyncratic dynamics is reflected in the second principal component (PC2) and we thus use it to analyze the group-specific characteristics. The loadings associated with PC2 provide insight into the interrelation of the individual uncertainty measures. We obtain positive loadings for survey disagreement iqr^s and ent^s (0.34 and 0.44). That is, survey disagreement is governed by noticeable idiosyncratic movements. In contrast, PC2 loads negatively on the two forecast-based disagreement measures iqr^f and ent^f (-0.56 and -0.57). From the opposite signs of the loadings, we infer that PC2 represents a factor that drives survey-based and forecast-based measures into opposite directions; the other measures do not contribute to PC2 significantly.

The left panel of Figure 1.5 depicts PC2, which is far from being white noise. To identify situations where survey-based and forecast-based disagreement measures move less synchronized, we analyze the contemporaneous correlations of PC2 to economic variables in Table 1.2. In opposition to PC1, PC2 tends to co-move with the business cycle as we obtain a positive correlation with the Purchasing Manager Index (*pmi*) and negative correlations with all unemployment related variables. Hence, the idiosyncratic part of iqr^s and ent^s decreases during a downswing while the idiosyncratic part of iqr^f and ent^f tends to rise. Similarly, a rise in commodity prices is associated with an increase in PC2, probably reflecting the fact that these prices tend to co-move with the business cycle. Overall, survey disagreement and the forecast-based disagreement measures tend to drift apart during economic downturns.

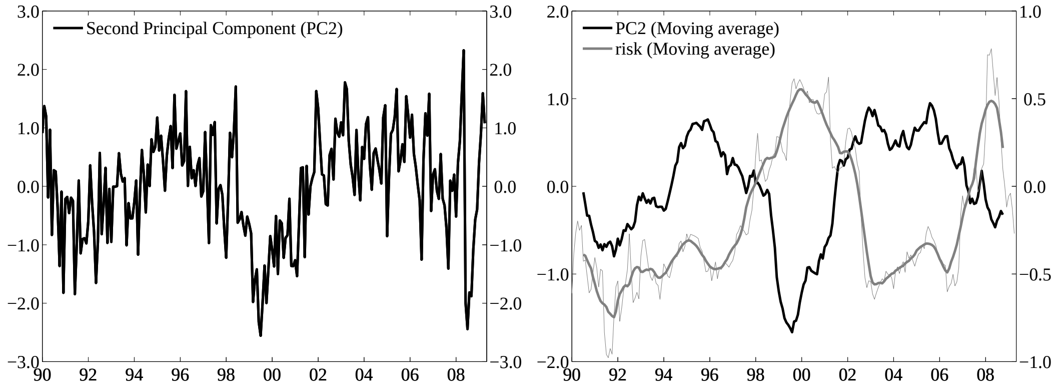
Table 1.2: Correlations of Principal Components with Economic and Financial Variables

		PC1	PC2
Consumer prices	$(\Delta\pi)^2$	**0.40**	**0.14**
	$(\Delta\pi^{core})^2$	**0.18**	−0.14
Money aggregate	$\Delta M2$	**0.16**	**0.21**
	$(\Delta M2)^2$	**0.33**	**0.15**
Interest rates	ffr	−0.45	−0.24
	r^{3M}	−0.48	−0.24
	r^{10Y}	−0.23	−0.33
	Δffr	−0.27	
	Δr^{3M}	−0.18	
	Δr^{10Y}		
	$abs(\Delta ffr)$		−0.17
	$abs(\Delta r^{3M})$		−0.13
	$abs(\Delta r^{10Y})$	**0.37**	
Financial market risk	vix	**0.51**	
	ted	**0.30**	
	$risk$	**0.35**	−0.20
Stock prices	$sp500$		
	dj		
	$dj5000$		
	$sp500^2$	**0.24**	
	dj^2	**0.21**	
	$dj5000^2$	**0.24**	
House prices	$house$	−0.64	**0.18**
	$\Delta house$		−0.17
	$(\Delta house)^2$	**0.47**	**0.14**
NBER dates	$recession$	**0.58**	

		PC1	PC2
Commodity prices	wti	−0.13	
	ppi^{comm}	−0.19	**0.23**
	ppi^{ind}	−0.19	**0.20**
	crb^{return}	−0.32	**0.28**
	$(\Delta wti)^2$	**0.21**	
	$(\Delta ppi^{comm})^2$	**0.47**	**0.16**
	$(\Delta ppi^{ind})^2$	**0.43**	**0.15**
	$(\Delta crb^{return})^2$	**0.39**	**0.18**
Business activity	ism	−0.47	
	ism^{prod}	−0.42	
	pmi	−0.53	**0.20**
	pmi^{prod}	−0.56	**0.15**
Consumer climate	mhs	−0.81	
	$confidence$	−0.61	
Capacity utilization rate	cu	−0.67	
	cu^{man}	−0.69	
	cu^{exIT}	−0.74	
Production and employment	Δy	−0.81	
	Δy^{man}	−0.82	
	$(\Delta y)^2$	**0.55**	−0.22
	$(\Delta y^{man})^2$	**0.59**	−0.20
	$\Delta empl$	−0.77	
	$\Delta jobless$	**0.66**	−0.17
	Δu	**0.79**	−0.16
	ur	**0.55**	−0.14
	Δur	**0.80**	−0.15

Notes: Positive correlations are printed in bold and negative correlations are in lightface. Correlations that are insignificant at the 5% level do not appear in the Table. A detailed description of economic variables is given in Table 1.6 in appendix 1.B.

Figure 1.5: Second Principal Component (PC2)



Notes: In the right panel, the bold lines show a twelve month moving average of the second principal component (black line, left axis) and the log of the corporate bond risk premium (gray line, right axis). The thin lines represent the unfiltered data.

Moreover, PC2 decreases when the corporate bond risk premium ($risk$) or the output variability increases. Note that both variables are indicators for overall economic risk (see, for instance, Bachmann, Elstner, and Sims, 2013). As contemporaneous correlations neglect dynamic relations, we plot PC2 along with the corporate risk premium in the right panel of Figure 1.5. For illustration purposes, we smooth both series by taking a twelve-month centered moving average. We observe that the risk premium and PC2 move in opposite directions. The pronounced drop of PC2 around the year 2000 especially coincides with a distinct increase of overall economic risk. Once the risk premium starts to come down, PC2 escalates and remains at a high level while economic risk stays low until 2007. Thus, survey-based and forecast-based disagreement measures tend to drift apart during economically turbulent times such that the idiosyncratic part of iqr^s and ent^s decreases while the idiosyncratic part of iqr^f and ent^f mounts.

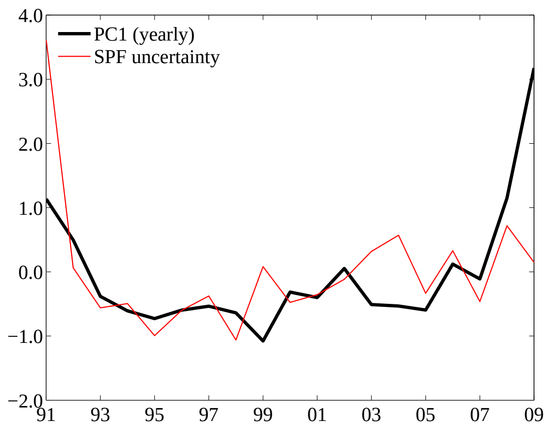
For an interpretation of the above findings, we draw attention to the conceptual ideas behind these measures. First, note that forecast-based and survey-based disagreement measures are conceptually similar because both rely on a number of different forecasts. In particular, we may interpret the multitude of VAR models as a panel of forecasters where each forecaster uses a different VAR model. A conceptual discrepancy arises from the fact that the forecast-based approach provides a purely mechanistic way to deal with heterogeneous information. As a consequence, forecasts from different VAR models almost inevitably diverge when indicators provide heterogeneous signals. By contrast, in a survey, the way information is combined into a forecast is to a non-negligible extent governed by subjective elements. For instance, the choice of a particular forecast model, the weights attached to different pieces of information, or judgmental adjustments may influence the forecast reported. If forecasters are risk-averse, they may choose to stick to the consensus if uncertainty is high, and forecast dispersion may decline. Thus, an explanation for the divergence of survey-based disagreement and forecast-based disagreement is that forecasters may cluster their forecasts around the consensus during turbulent times. This typically does not happen to the forecast-based measures. Being a mechanistic approach, forecast-based disagreement, in fact, appears to overstate "true" inflation uncertainty. Overall, our results suggest that using only one individual disagreement measure may be misleading during turbulent times. Note that this finding is also consistent with the theoretical considerations by Lahiri and Sheng (2010b), who assume that individual forecast errors are driven by common and idiosyncratic shocks. Under these assumptions, they show that disagreement is a reliable proxy for overall uncertainty only during stable periods; i.e., whenever the shocks common to all forecasters are small.

1.3.4 Comparison to SPF Inflation Uncertainty

Many studies use uncertainty measures based on the SPF (Zarnowitz and Lambros, 1987, Lahiri, Teigland, and Zaporowski, 1988, Batchelor and Dua, 1993, 1996, Giordani and Söderlind, 2003, Chua, Kim, and Suardi, 2011). The reason is that the SPF provides individual histograms of expected inflation. Due to this specific survey design, we can derive for each forecaster i the individual standard deviation σ_i of the inflation forecast. The average over individual standard deviations provides an obvious measure of overall inflation uncertainty (Giordani and Söderlind, 2003).

Ideally, our uncertainty indicator presented in Section 1.3.2 should incorporate information from SPF uncertainty as well. However, this is not feasible since the SPF is conducted quarterly. Furthermore, SPF predictive densities relate to fixed-event forecasts. Hence, a one-year horizon is polled only in the first quarter of a year. As the forecast horizon shrinks in the subsequent quarters of the year, the uncertainty surrounding the respective forecast also declines. Nevertheless, we compare PC1 to SPF uncertainty but have to restrict our comparison to yearly observations. Since one-year-ahead SPF forecasts are usually published at the end of the first quarter, we compare the value of SPF uncertainty with the value of PC1 in March of a respective year. To calculate forecaster-specific uncertainty σ_i, we follow D'Amico and Orphanides (2008), and Lahiri and Sheng (2010b) and use a non-parametric procedure. We obtain SPF uncertainty as the average of individual standard deviations adding a Sheppard correction. Figure 1.6 depicts the resulting time series, which are both normalized to have mean zero and standard deviation one.

Figure 1.6: Yearly Uncertainty Indicator (PC1) and SPF Uncertainty



SPF uncertainty moves rather abruptly with a spike in the year 1991 followed by a decline and an upward movement in the last decade. In contrast, PC1 appears to be more persistent whereas the recent hike is more pronounced. The first-order autocorrelation coefficient amounts to 0.41 for yearly data of PC1 whereas it is practically zero (0.09) for SPF uncertainty. Nevertheless, our uncertainty indicator and SPF uncertainty co-move at large, and the correlation coefficient is 0.45. We also compare SPF uncertainty to the individual measures, and we obtain a positive correlation for all measures. Moreover, PC1 has a higher correlation with SPF uncertainty than most of the individual measures.[15]

Some limitations of such a comparison have to be noted. First, SPF uncertainty refers to the GDP deflator as opposed to CPI inflation since probability forecasts for the CPI inflation rate are not available before 2007. Moreover, a number of assumptions have to be made to derive an uncertainty measure from SPF forecast histograms (see, for instance, D'Amico and Orphanides, 2008, Rich

[15] The survey-based measures iqr^s and ent^s are also highly correlated with SPF uncertainty, which may be explained by the fact that these measures are also derived from a professional forecasters' survey. For detailed results and a graphical representation, see Figure 1.9 in appendix 1.C.

and Tracy, 2010). Furthermore, changes in the survey design concerning, for example, the number and the width of histogram bins may distort the signal. Overall, SPF uncertainty is very likely subject to idiosyncratic measurement error – as any other measure – which may explain a temporary divergence of SPF uncertainty and PC1 (also compare Batchelor and Dua, 1993, 1996).

1.4 The Link between Inflation and Inflation Uncertainty

The link between inflation and inflation uncertainty has recently gained renewed relevance with the call for temporary higher inflation rates to mitigate the problem of debt overhang. From a theoretical point of view, Friedman (1977) argues that high inflation rates are less predictable than lower rates. Ball (1992) formalizes the idea stating that inflation uncertainty increases in the event of higher inflation because the policy response is harder to predict (Friedman-Ball hypothesis). In contrast, Cukierman and Meltzer (1986) argue that the link is from inflation uncertainty to inflation. In a Barro-Gordon framework, they claim that, with highly uncertain agents, the central bank has an incentive to create surprise inflation to lower unemployment.

We use both PC1 and the individual measures to investigate the link between inflation and inflation uncertainty. If we are able to remove the idiosyncratic component from the individual measures, PC1 should yield a more precise and robust estimate of the relation between inflation and inflation uncertainty since it summarizes the information in the individual measures. To further examine whether PC1 is a valid measure of uncertainty, we analyze the sign of the relation between inflation and inflation uncertainty. Note that both theories, Friedman-Ball and Cukierman-Meltzer, suggest that both variables co-move over time. Although it is impossible to directly show that PC1 retraces the movements of the unobserved "true" inflation uncertainty, we should be able to establish a positive link if PC1 is a valid measure of inflation uncertainty.

First, we test the inflation-inflation uncertainty link by means of a Granger causality test. To this end, we estimate bivariate VAR models containing inflation and one uncertainty measure. As we deal with monthly data, the lag length is set to 12. Results of a Granger causality test are presented in Table 1.3. The p-values reveal a strikingly inconclusive picture. $rmse^s$ and iqr^f seem to be Granger caused by inflation, yet not vice versa, whereas for iqr^s Granger causality appears to hold for both directions. For ent^s, ent^f, and $garch$, we find no dynamic relation to inflation. In the case of $rmse^f$ and $ucsv$, uncertainty is followed by inflation. When the same test is conducted for the change of inflation, we obtain similar results. Overall, it appears that the choice of the measure is crucial. Thus, using individual measures entails the risk that results are driven by idiosyncratic movements that are unrelated to inflation uncertainty.

Table 1.3: Granger Causality Test for Inflation Uncertainty and Inflation

	PC1	irq^s	ent^s	$rmse^s$	iqr^f	ent^f	$rmse^f$	$garch$	$ucsv$
H_0: π does not Granger cause IU	**0.00**	**0.00**	0.08	**0.02**	**0.02**	0.58	0.07	0.07	0.91
H_0: IU does not Granger cause π	0.39	**0.01**	0.31	0.27	0.17	0.29	**0.01**	0.50	**0.03**
H_0: $\Delta\pi$ does not Granger cause IU	**0.00**	**0.00**	0.30	**0.02**	**0.01**	0.64	0.07	**0.01**	0.90
H_0: IU does not Granger cause $\Delta\pi$	0.29	0.19	0.14	**0.01**	**0.00**	**0.01**	**0.00**	0.19	**0.02**

Notes: Granger causality tests are performed for inflation π as well as the monthly change of inflation $\Delta\pi$ and inflation uncertainty (IU). Numbers are p-values for a Granger causality test performed by means of a joint F-Test. The lag length of each VAR model is set to 12. Sample ranges from $1990M09$ to $2009M12$.

Using PC1 to measure inflation uncertainty, we find that inflation Granger causes inflation uncertainty but not vice versa. Although Granger causality is only a prerequisite for economic causality, such a result is in favor of the Friedman-Ball hypothesis. The same result is obtained if we consider the change in inflation.[16] Most notably, results in Table 1.3 suggest that PC1 provides an insurance against idiosyncratic measurement error attached to the individual measures.

Second, we assess the sign of the effect of an exogenous increase in inflation on inflation uncertainty. We take a dynamic perspective and calculate impulse response functions from the bivariate VAR models introduced above. Orthogonal shocks are identified using a Cholesky ordering such that uncertainty instantaneously reacts to a shock to inflation.[17] This is motivated by the fact that uncertainty may move quickly when agents encounter new macroeconomic information whereas inflation is comparatively slow-moving.

The left panel of Figure 1.7 presents the response of the uncertainty indicator PC1 to a one standard deviation shock to inflation. Following an inflation

[16] The result is robust to the choice of the lag length of the VAR according to BIC, which suggests two lags. Furthermore, it is robust if we exclude the recent crisis and end the sample in 2007:M8, which is roughly when the U.S. subprime crisis started to spill over into other sectors of the economy.

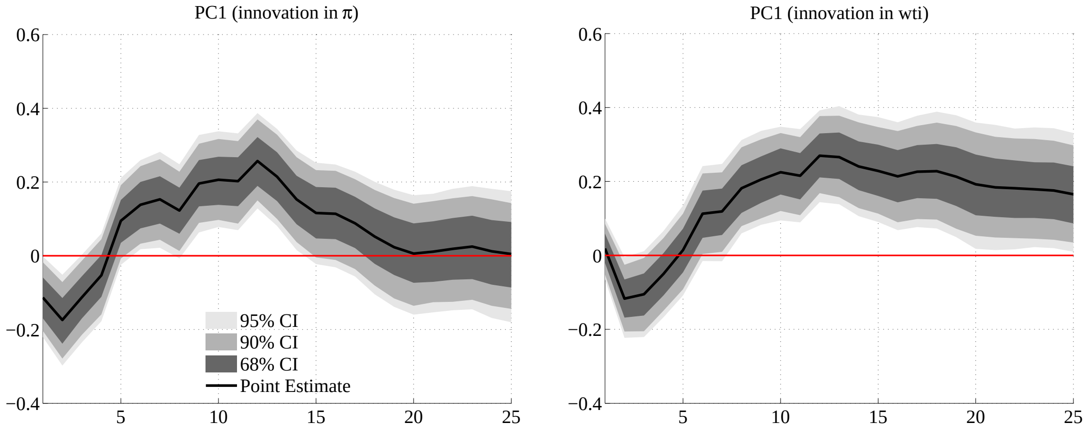
[17] We also checked the reverse ordering of variables, which does not affect the results in a significant way.

shock, we observe that uncertainty experiences an initial significant decline for about two months. In other words, directly after the shock, a forecast for subsequent periods seems to be less uncertain. This may be due to the fact that – given the sluggishness of inflation – a forecast is relatively easy in the period directly following the inflation shock. Let us consider an inflation shock that is the result of a sudden increase in oil prices. Having observed the shock, this very likely decreases uncertainty associated with future inflation. The reason is that forecasters may be relatively sure to observe an increase in inflation rates during the first few months after the shock. In the following periods, inflation uncertainty displays a hump-shaped pattern. It quickly increases and becomes significantly positive about five months after the shock occurred. Thus, the more time that has elapsed since the shock, the more uncertainty is attached to the future course of inflation. Again, let us consider a sudden increase in oil prices. In this case, uncertainty accumulates over time because the long-term effects of such an inflation shock – e.g. via second round effects – are less clear-cut. The response of uncertainty to a shock to oil price inflation (wti) is depicted in the right panel of Figure 1.7. The pattern of the impulse response function very much resembles the response of PC1 to an innovation in inflation. Hence, the plot confirms the hypothesis that the short-term impact of increasing oil prices seems to be relatively clear-cut, whereas longer lasting effects on the inflation rate are uncertain.[18]

Turning to Figure 1.8, we observe that a shock to core inflation (π^{core}) also induces a rise in uncertainty. Here, it takes about four months until uncertainty increases. In contrast to CPI inflation, a shock to core inflation does not induce a fall in uncertainty in the first periods. We take this as further evidence that the initial decrease in uncertainty after a shock to CPI inflation is traceable to the energy component in CPI. That is, once an energy price shock has materialized, the short-run impact of this shock on inflation seems to be well known, and consequently reduces forecast uncertainty. In the long run, however, the rise in uncertainty is even more pronounced after a shock to CPI inflation than after a core inflation shock. Notably, following a one-time increase in core inflation, uncertainty persistently remains on a higher level.

[18] See appendix 1.E for results obtained from monetary VARs containing output, inflation, a short-term interest rate, and uncertainty. Our results remain unaffected when a larger VAR is employed. Furthermore, the impulse response is qualitatively the same when we estimate the bivariate VAR on a sample ending in 2007:M8; this result is available upon request.

Figure 1.7: Response of Inflation Uncertainty to Inflation and wti



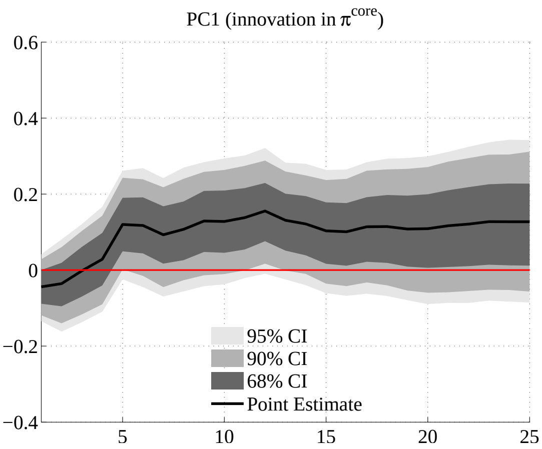
Notes: Confidence intervals are obtained from a bias adjusted bootstrap procedure (Kilian, 1998).

We document a significant increase of inflation uncertainty following an inflation shock. That is, PC1 co-moves with inflation. We highlight that the increase is probably due to growing uncertainty about the transmission of a shock. In addition, increased inflation uncertainty may also be the result of rising uncertainty about the reaction of the central bank. The latter scenario is very much in the spirit of Friedman (1977), who recognizes that, given rising rates of inflation, economic agents become more and more uncertain about the timing and pace at which inflation will return to lower levels again. Overall, PC1 delivers results consistent with standard theory on the inflation-inflation uncertainty link. Such a finding provides evidence to support the claim that PC1 is a valid measure. In contrast, when we repeat the exercise for each individual uncertainty measure, we find that the response of uncertainty is rather heterogeneous.[19] Hence, the link from inflation to inflation uncertainty is not revealed in a conclusive way if we rely on a single measure.

Finally, we analyze whether the contribution of inflationary shocks to PC1 is meaningful in an economic sense. To this end, Table 1.4 presents the forecast error variance decomposition associated with the bivariate VAR models shown in Figures 1.7 and 1.8. We find that an inflation shock explains roughly 21% of the forecast error variance of inflation uncertainty after 15 months. With a value of only 7.7% after 15 months, core inflation (π^{core}) explains less than headline inflation suggesting that the energy component in the CPI is a major determinant of inflation uncertainty. Likewise, the contribution of oil price inflation

[19] Only two of the responses (iqr^s and $rmse^f$) are similar to the response of PC1. The individual impulse responses are presented in Figure 1.10 in appendix 1.D.

Figure 1.8: Response of Inflation Uncertainty to Core Inflation



Notes: Confidence intervals are obtained from a bias adjusted bootstrap procedure (Kilian, 1998).

(wti) peaks in the longer run at about 22%, which confirms the importance of oil price movements for uncertainty.

Table 1.4: Forecast Error Variance Decomposition

horizon	**1**	**5**	**10**	**15**	**20**	**25**
π	3.2	6.8	14.0	20.6	15.2	10.7
wti	0.1	2.8	11.8	22.2	21.6	19.8
π^{core}	0.4	1.5	4.7	7.7	7.4	7.6

Notes: Numbers (as % of total variance) give the part of the variance of inflation uncertainty explained by a shock to the respective economic variable. The respective values are derived from bivariate VAR models. Variance decompositions are presented for a horizon of 1, 5, 10, 15, 20, and 25 months.

1.5 Concluding Remarks

After analyzing various measures of inflation uncertainty, we document that inflation uncertainty has risen significantly in the aftermath of the recent financial crisis. This finding, together with the recent calls for higher inflation to mitigate the problem of debt overhang, highlights the importance of understanding the relationship between inflation and inflation uncertainty. However, empirical results derived from different measures are ambiguous. An explanation is that each individual measure is derived from different assumptions which are very likely not fulfilled completely. Hence, individual measures may be contaminated by idiosyncratic measurement error.

We use common information in different uncertainty measures to eliminate the idiosyncratic measurement error. To this end, we calculate survey-based measures as well as measures derived from time series models, and we propose a forecast-based approach. We find that all measures – including disagreement – are driven by a common component, which we interpret as an indicator for inflation uncertainty. Notably, the indicator helps to overcome the idiosyncratic measurement error problem, and the underlying signal should be revealed with greater precision. Moreover, we find that the loadings of the individual measures on the common component are approximately equal. Therefore, taking a simple average over the individual measures is a viable alternative which delivers a robust indicator of inflation uncertainty.

Our indicator does not completely explain the variation in the data. In general, individual measures tend to differ more during turbulent times. From the idiosyncratic dynamics not captured by the common component, we infer that a researcher may be confronted with survey respondents sticking to the consensus when macroeconomic risk is high, which induces a downward bias in survey disagreement. In contrast, forecast-based disagreement might overstate "true" inflation uncertainty. Hence, using only one individual disagreement measure is a risky strategy.

Subsequently, we use the proposed uncertainty indicator to analyze the inflation - inflation uncertainty link. It appears that Granger causality tests are in favor of the Friedman-Ball hypothesis. We also study the dynamic response of uncertainty to an inflation shock. We document that uncertainty initially decreases and shows a swift increase in subsequent periods. This behavior is traceable to the energy component in CPI inflation. A sudden rise in the oil price, for instance, is followed by an initial decrease in inflation uncertainty. In the longer run, uncertainty eventually rises because long-term effects of these oil price increases appear to be harder to predict. Overall, we demonstrate that higher inflation is followed by higher uncertainty. However, we are aware of the difficulty of inferring causality by empirical testing only. In future research, it would certainly be fruitful to increase the effort to integrate inflation uncertainty into a structural macroeconomic model in order to establish a causal economic relationship.

Appendix

1.A Dataset to Estimate Forecast-Based Measures

Table 1.5: Variables Used to Forecast Inflation

Variable	Transformation
Average hourly earnings (nonfarm payroll)	change of growth rate
Building permits for new private housing units	growth rate
Capacity utilization (manufacturing)	growth rate
Crude oil index	change of growth rate
Employment (non-agricultural industries)	gap measure
Federal funds effective rate	growth rate
Interest rate spread	–
M3	change of growth rate
New orders (manufacturing)	growth rate
Nominal narrow effective exchange rate	growth rate
OECD composite leading indicators	growth rate
Personal income	growth rate
Retail sales	growth rate
Total production	gap measure
Unemployment rate	gap measure

Notes: "gap measure" denotes series that have been detrended with the HP-filter; "interest rate spread" is defined as the difference between interest rate on government bonds and federal funds rate.

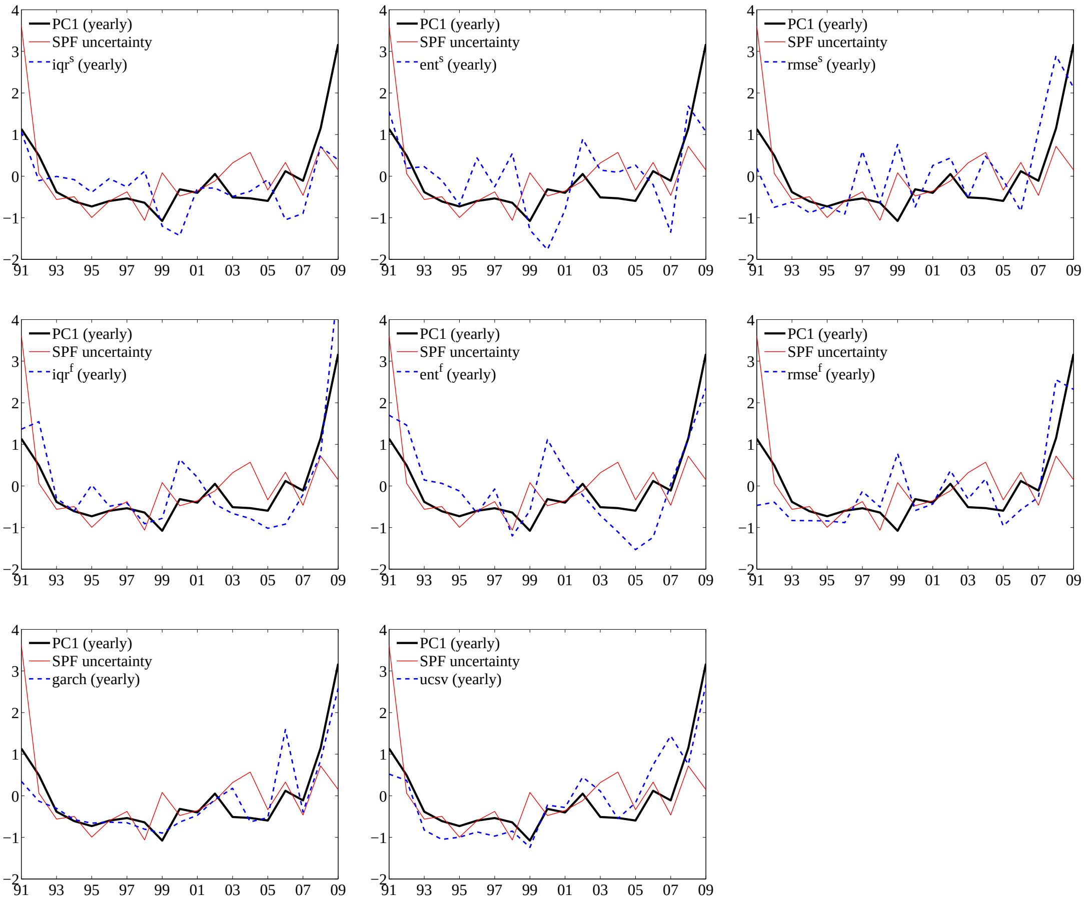
1.B Description of Variables

Table 1.6: Description of Economic Variables

Variable	Description	Variable	Description
$(\Delta\pi)^2$	Squared change of inflation	wti	Oil price inflation - West Texas Intermediate spot price for crude oil
$(\Delta\pi^{core})^2$	Squared change of core inflation	ppi^{comm}	Producer price inflation - Commodities
$\Delta M2$	MoM change of M2 money supply	ppi^{ind}	Producer price inflation - Industrial commodities
$(\Delta M2)^2$	Squared change of M2 money supply	crb^{return}	Commodity price inflation - Reuters/CRB total return index
ffr	Federal funds rate	$(\Delta wti)^2$	Squared change of WTI oil price
r^{3M}	3-month treasury bill rate	$(\Delta ppi^{comm})^2$	Squared change of producer price inflation (commodities)
r^{10Y}	10-year government benchmark, average yield	$(\Delta ppi^{ind})^2$	Squared change of producer price inflation (industrial commodities)
Δffr	MoM change of federal funds rate	$(\Delta crb^{return})^2$	Squared returns Reuters/CRB total return index
Δr^{3M}	MoM change of 3-month treasury bill rate	ism	ISM manufacturing total index
Δr^{10Y}	MoM Change of 10-year government benchmark rate	ism^{prod}	ISM manufacturing production index
$abs(\Delta ffr)$	Absolute change of federal funds rate	pmi	Chicago PMI total index of business activity
$abs(\Delta r^{3M})$	Absolute change of 3-month T-Bill	pmi^{prod}	Chicago PMI production index of business activity
$abs(\Delta r^{10Y})$	Absolute change of 10-year government benchmark rate	mhs	Consumer survey index - Michigan Household Survey
vix	CBOE Market volatility index	$confidence$	Consumer confidence index - Conference board
ted	Difference between interest rates on interbank loans and treasury bill rate	cu	Capacity utilization rate, total industry
$risk$	Difference between interest rates on corporate bonds and government benchmarks	cu^{man}	Capacity utilization rate, manufacturing
$sp500$	Standard & Poor's 500 Index returns	cu^{exIT}	Capacity utilization rate, manufacturing excluding IT
dj	Dow Jones Index returns	Δy	Change of monthly index of industrial production
$dj5000$	Dow Jones 5000 Index returns	Δy^{man}	Change of monthly index of manufacturing production
$sp500^2$	Squared returns Standard & Poor's 500 Index	$(\Delta y)^2$	Squared change of industrial production
dj^2	Squared returns Dow Jones Index	$(\Delta y^{man})^2$	Squared change of manufacturing production
$dj5000^2$	Squared returns Dow Jones 5000 Index	$\Delta empl$	Change of nonfarm-payroll employment
$house$	House price inflation by S&P/Case-Shiller	$\Delta jobless$	Change of initial jobless claims
$\Delta house$	MoM change of house price inflation	Δu	Change of unemployment
$(\Delta house)^2$	Squared change of house price inflation	ur	Unemployment rate
$recession$	NBER recession dummy (recession: 1, no recession: 0)	Δur	Change of unemployment rate

1.C Comparison of Individual Uncertainty Measures to SPF Inflation Uncertainty

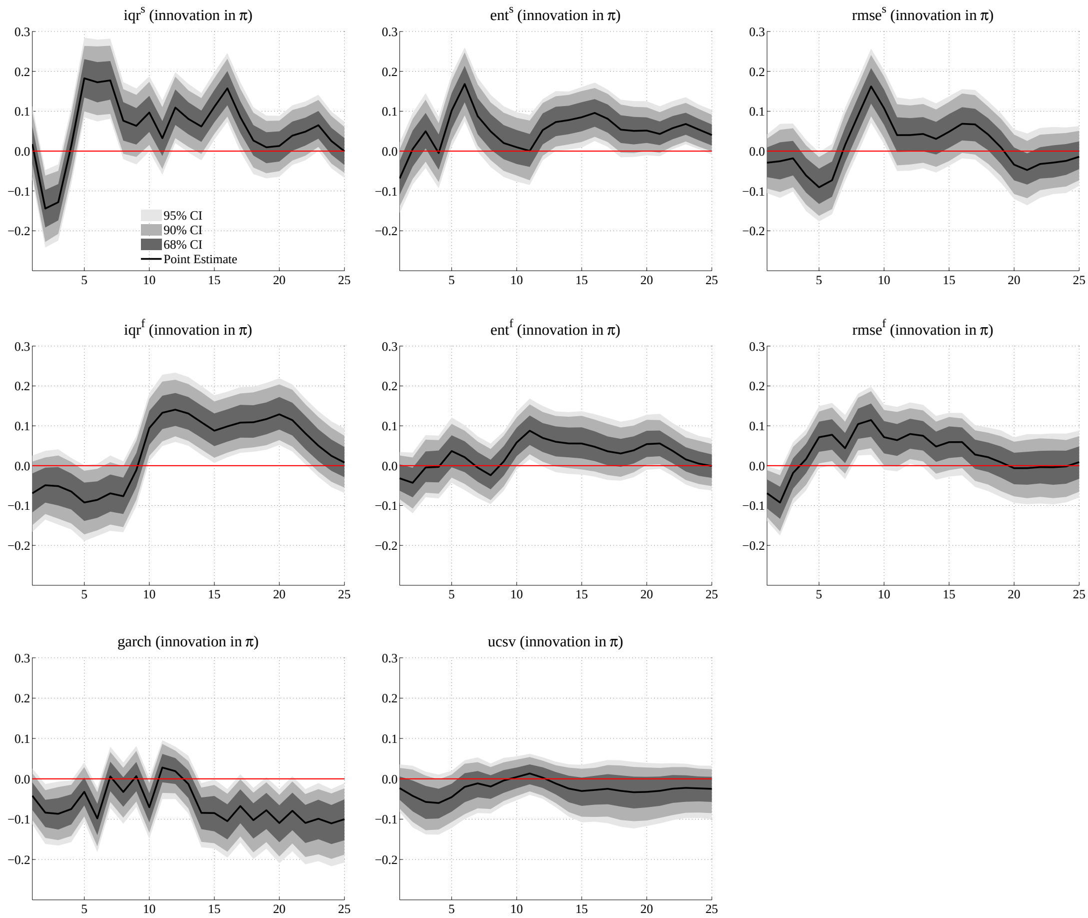
Figure 1.9: Yearly Individual Uncertainty Measures and SPF Uncertainty



Notes: Correlation coefficients of the yearly individual uncertainty measures and SPF uncertainty are, respectively, 0.48 (iqr^s), 0.50 (ent^s), 0.27 ($rmse^s$), 0.29 (iqr^f), 0.39 (ent^f), 0.22 ($rmse^f$), 0.36 ($garch$), and 0.33 ($ucsv$).

1.D Impulse Responses of Individual Uncertainty Measures

Figure 1.10: Impulse Responses of Individual Uncertainty Measures

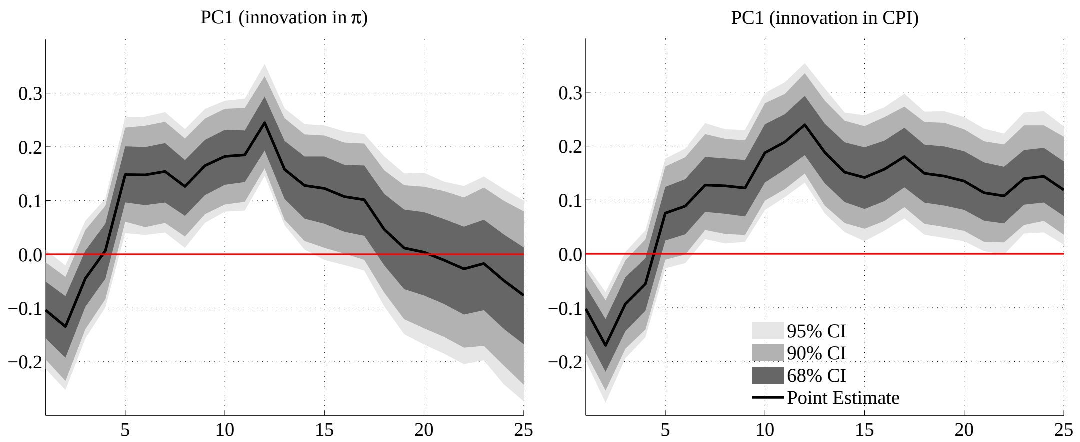


Notes: Confidence intervals are obtained from a bias adjusted bootstrap procedure (Kilian, 1998).

1.E Alternative VAR Specifications

In the following, we analyze whether the response of uncertainty to an inflation shock is robust to alternative VAR specifications. To this end, we specify a larger VAR model which is standard for monetary policy analysis. It includes monthly data on industrial production, consumer prices, the federal funds rate, and inflation uncertainty. Note that inflation uncertainty is ordered last. We consider two alternatives. First, all variables except the interest rate enter in log-levels. Second, we include production growth and inflation instead of production and the price level. The resulting impulse response functions are presented in Figure 1.11. Our results remain unaffected by the inclusion of additional variables.

Figure 1.11: Response of Inflation Uncertainty to a CPI Shock (left) and to an Inflation Shock (right) in a 4-Variable VAR



Notes: Confidence intervals are obtained from a bias adjusted bootstrap procedure (Kilian, 1998).

CHAPTER 2

Time-Varying Business Volatility, Price Setting, and the Real Effects of Monetary Policy

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

2.1 Introduction

Does time-varying business volatility affect the price setting of firms and thus the real effects of monetary policy? A fundamental result of New Keynesian macroeconomics is that, due to price stickiness, changes in monetary policy affect real variables in the short run. If heightened volatility or uncertainty were to change the degree of price rigidity, this would directly influence monetary policy transmission. This channel is potentially important as price flexibility seems to be countercyclical in the data. This is shown by Vavra (2014) for U.S. consumer price data, and we confirm this finding with producer price data from the West German manufacturing sector. This means that prices seem to become more flexible and, possibly, monetary policy less effective in times when monetary stabilization is perhaps most needed.

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

The impact of volatility and uncertainty on the macroeconomy and macroeconomic policy-making, in particular monetary policy, is a question of longstanding interest. An early debate started with the seminal contribution by Brainard (1967) that investigates how model (or parameter) uncertainty should influence monetary policy. While the so-called Brainard Principle prescribes caution in policy making when encountering uncertainty (see also Zakovic, Wieland, and Rustem, 2007, for a more recent contribution), other authors using minmax analysis (e.g., Sargent, 1999) find that increases in economic uncertainty should lead to more aggressive responses by the policymaker. Another strand of the literature has investigated the consequences of another type of volatility/uncertainty, namely, heteroskedasticity in the shock processes affecting the macroeconomy. An early contribution here is Bernanke (1983). More recently, since the beginning of the financial crisis in the U.S., there has been a renewed interest in the consequences of volatility/uncertainty for economic activity starting with Bloom (2009). This growing literature, to which this paper broadly belongs, 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, 2013, 2014, Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry, 2012), financial frictions (e.g., Christiano, Motto, and Rostagno, 2014, Gilchrist, Sim, and Zakrajsek, 2014, Arellano, Bai, and Kehoe, 2012), 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, Guerrón-Quintana, Rubio-Ramírez, and Uribe, 2011) and fiscal policy volatility (e.g., Born and Pfeifer, 2014, Fernández-Villaverde, Guerrón-Quintana, Kuester, and Rubio-Ramírez, 2012, Baker, Bloom, and Davis, 2013).

The consequences of heightened volatility for the price-setting decisions of firms and thus, by extension, for monetary policy, however, have remained largely unexplored. In a recent contribution, 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.[20] Theoretically, heightened business volatility can have two effects. First, to the extend that volatility also constitutes uncertainty for firms and adjusting prices is subject to some degree of irreversibility, firms may want to "wait and see", refrain from adjusting their prices and, thus, prices become endogenously more sticky. Second, higher volatility makes price adjustment of firms more likely as firms on average are hit by larger shocks. Hence, the sign of the relationship between firm-level volatility and likelihood of price adjustment is an empirical question which has thus far not been studied in the literature. This paper fills this gap. Vavra (2014), in the context of a calibrated Ss price-setting model, analyzes the importance of both effects and shows that in his calibration the volatility effect dominates. Heightened volatility would therefore trigger an increase in the frequency of price adjustment and would make monetary policy less effective. In a related paper, Baley and Blanco (2013) build a pricing model with endogenous uncertainty generated by an information friction at the firm level and learning. Specifically, firms have imperfect information about their nominal costs which they have to forecast. The authors show that an increase in uncertainty makes firms learn more, makes them more responsive

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

to new (noisy) information and, hence, leads them to adjust their prices more frequently.[21]

The novel contribution of this paper is to compute measures of firm-specific volatility and to estimate and quantify directly the impact of heightened firm-level volatility on the firms' price setting behavior. These business volatility measures are constructed from the confidential micro data in the IFO Business Climate Survey (IFO-BCS). Survey micro data are well-suited for our research question as they are based on statements from actual decision-makers at the firms as opposed to, for example, outside analysts. This means that our measures of business volatility will also capture uncertainty at the firm level and thus allow the "wait-and-see" effect caused by uncertainty to shine through. Survey data are also less likely to suffer from strategic behavior, such as, e.g., public earnings announcements, as they are highly confidential and can only be accessed under strict non-disclosure agreements. The unique feature of the German IFO-BCS is that it allows us to construct firm-specific volatility measures and that it contains information on the price setting behavior of the same firms. 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, Elstner, and Sims (2013) and Bachmann and Elstner (2013). Bachmann, Elstner, and Sims (2013) construct expectation errors at the firm level, based on qualitative survey questions. We use the absolute value of these expectation errors as one of our measures for instantaneous idiosyncratic volatility. The advantage of this qualitative measure is that it can be constructed for a relatively large sample of firms. However, they only allow us to evaluate the sign of the relationship between volatility and price setting at the firm-level. Therefore, we compute for a subset of firms a quantitative volatility measure in line with Bachmann and Elstner (2013) from firm statements about capacity utilization. With this quantitative volatility measure we then assess the magnitude of the effect of idiosyncratic volatility on the price setting behavior of firms and use this elasticity as an input into a fully calibrated structural model.

The second strategy is based on the same qualitative and quantitative expectation errors but, instead of the absolute expectation error, uses a firm-specific rolling window standard deviation as in Comin and Mulani (2006) and Davis, Haltiwanger, Jarmin, and Miranda (2006). We show that volatility measures

[21] This result is also in line with the "rational inattention"-literature (see, e.g., Mackowiak and Wiederholt, 2009, forthcoming), which finds that more volatile environments lead to more frequent updating of prices.

based on either procedure are highly correlated and that our substantive results are robust across these different specifications.

In order to assess to what extent heightened firm-level volatility affects the frequency of price adjustment, we estimate a probit model on a panel of (on average) 2,500 German firms from January 1980 to December 2011. Our results confirm that heightened volatility increases the frequency of price changes. For example, the tripling of volatility during the recession of 08/09 – an increase of about 6 standard deviations – caused the average quarterly likelihood of a price change to increase from 31.6% to 32.3%. This means that we confirm the theoretical predictions from Vavra (2014), Baley and Blanco (2013), and the rational inattention literature directly in the data.

After having established the link between price setting and idiosyncratic volatility in our survey data, we use an off-the-shelve New Keynesian DSGE model (see, e.g., Galí, 2008), where price setting is constrained à la Calvo (1983), to flesh out the impact of heightened volatility on the effectiveness of monetary policy. Using the uncovered empirical relationship between an increase in firm-specific volatility and the probability of a price change, we then capture a change in firm-specific volatility through a change in the Calvo parameter.

Our results show that, even though idiosyncratic volatility was at the trough of the 08/09-recession roughly three times higher than on average before, the resulting effect on the frequency of price adjustment is small. During this time, a monetary stimulus of a 25 basis point cut in the nominal interest rate, would have lost about 1.6 percent of its effect on real output, with the impact effect decreasing from 0.347% to 0.341%. However, while heightened business volatility in isolation would not have led to a large increase in price flexibility in the 08/09-recession, we observe an overall increase in the average share of firms adjusting their price by about 7 percentage points in the same time period. Such a sizable increase in price flexibility would have translated into a decline in the output impact effect of a 25 basis point monetary policy shock from 0.346% to 0.289%, a decrease of almost 17 percent. Hence, while changes in price flexibility over the business cycle are potentially an important issue for the conduct of monetary policy, we find little evidence that they are driven by changes in firm-level volatility.

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

2.2 Measuring Idiosyncratic Volatility

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

2.2.1 IFO Business Climate Survey

Table 2.1: Questionnaire

No.	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	$E(\textit{Production})$	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	$E(\textit{Price})$	Expectations for the next 3 months: Our net domestic sales prices for XY will …	increase	remain about the same	decrease
Q5	*Business Situation*	We evaluate our business situation with respect to XY as …	good	satisfactory	unsatisfactory
Q6	*Business Expectations*	Expectations for the next 6 months: Our business situation with respect to XY will in a cyclical view …	improve	remain about the same	develop unfavourably
Q7	*Orders*	Our orders with respect to product XY have …	increased	roughly stayed the same	decreased
Quarterly and Supplementary Questions					
Q8	*Capacity Utilization*	The utilization of our production equipment for producing XY currently amounts to … %.	30% ,40%,…,70%,75%,…,100%, more than 100%		
Q9	*Technical Capacity*	We evaluate our technical production capacity with reference to the backlog of orders on books and to orders expected in the next twelve months as …	more than sufficient	sufficient	less than sufficient
Q10	*Employment Expectations*	Expectations for the next 3 months: Employment related to the production of XY in domestic production unit(s) will probably …	increase	roughly stay the same	decrease

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

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

An attractive feature of the IFO-BCS is the relatively 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.[22] Participation in the survey is voluntary and there is some fraction of firms that are only one-time participants. However, conditional on staying two months in the survey, most firms continue to participate each month. In terms of firm size, about 9.4% of firms in our sample have less than 20 employees, roughly 32.0% have more than 20 but less than 100 employees, 47.3% employed between 100 and 1000 people, and 11.3% have a workforce of more than 1000.

The IFO-BCS, in its core, is a monthly qualitative business survey where firms provide answers that fall into three qualitative categories: *Increase*, *Decrease*, and a neutral category. The monthly part of the survey is supplemented on a quarterly basis with some quantitative questions, e.g., with respect to firms' capacity utilization. In our analysis we make use of a wide range of explanatory variables that might be relevant to the pricing decision of a firm. Table 2.1 summarizes these questions.

2.2.2 Construction of Qualitative Volatilty Measures

The construction of ex-post forecast errors combines past responses of the production expectation question (Q2) with current responses of realized production changes vis-à-vis last month (Q1). We follow Bachmann, Elstner, and Sims (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:[23] 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

[22] 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.

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

would quantify the expectation error as -1 and, finally, it could have realized a decrease, which counts as -2. Table 2.2 summarizes the possible expectation errors.

Table 2.2: 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.

In actuality, the production expectation question in the IFO-BCS is for three months ahead. Suppose that a firm stated in month $\tau - 3$ that its production will increase in the next three months. Suppose further that in the next three months one observes the following sequence of outcomes: production increased between $\tau - 3$ and $\tau - 2$, remained unchanged between $\tau - 2$ and $\tau - 1$, and production decreased between $\tau - 1$ and τ. Due to the qualitative nature of the IFO-BCS we have to make assumptions about the cumulative production change over three months. As a baseline we adopt the following steps. First, we define for each month τ a firm-specific activity variable as the sum of the *Increase* instances minus the 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 2.3.

Table 2.3: 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 2.3 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 $FE^{qual}_{i,\tau+3}$ as a measure of idiosyncratic volatility in period τ of firm i.[24] We denote this variable by $ABSFE^{qual}_{i,\tau}$:

$$ABSFE^{qual}_{i,\tau} = \left| FE^{qual}_{i,\tau+3} \right| . \tag{2.1}$$

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

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

$$STDFE^{qual}_{i,\tau} = \frac{1}{3}\sqrt{\sum_k \left(FE^{qual}_{i,\tau+3+k} - \overline{FE}^{qual}_{i,\tau+3} \right)^2} \tag{2.2}$$

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

2.2.3 Construction of Quantitative Volatility Measures

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

$$y^{act}_{i,\tau} = u_{i,\tau} y^{pot}_{i,\tau} \tag{2.3}$$

[24] The use of the absolute forecast error as a volatility proxy is motivated by the stochastic volatility model (see, e.g., Shephard, 2008, Fernández-Villaverde, Guerrón-Quintana, and Rubio-Ramírez, 2010, Fernández-Villaverde, Guerrón-Quintana, Rubio-Ramírez, and Uribe, 2011). In this model, the time-varying log standard deviations evolve according to $\sigma_t = (1-\rho)\,\bar{\sigma} + \rho\sigma_{t-1} + \eta\varepsilon_t$, where ε_t is an iid 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.

where $y_{i,\tau}^{act}$ denotes the firm's actual output, $y_{i,\tau}^{pot}$ its potential output level, and $u_{i,\tau}$ the level of capacity utilization. Only $u_{i,\tau}$ is directly observable in the IFO-BCS. Taking the natural logarithm and the three-month difference, we get[25]

$$\Delta \log y_{i,\tau}^{act} = \Delta \log u_{i,\tau} + \Delta \log y_{i,\tau}^{pot} \ . \tag{2.4}$$

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

If the production capacity can be assumed not to have changed in the preceding quarter, and if, in addition, no change in production was expected three months prior, a change in capacity utilization, $\Delta \log u_{i,\tau}$, is also a production expectation error of firm i in month τ. We thus consider only firms which state in period $\tau - 3$ that their production level (Q2), employment level, and technical production capacity will remain the same in the next three months.[27] We then

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

[26] 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.

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

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 $FE^{quan}_{i,\tau}$.[28]

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

$$ABSFE^{quan}_{i,\tau} = \left|FE^{quan}_{i,\tau+3}\right| \tag{2.5}$$

where $ABSFE^{quan}_{i,\tau}$ denotes our quantitative idiosyncratic volatility measure of firm i in period τ. Note that we can compute quantitative volatility measures only for firm level observations with constant production expectations as the question concerning production expectations (Q2) is qualitative. The quantitative nature of this measure allows us to give a quantitative interpretation of the relationship between idiosyncratic volatility and the price setting of firms that we can use for our quantitative theory work.

We also compute a 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.

2.2.4 Discussion of Volatility Measures

How do our measures of idiosyncratic volatility/uncertainty relate to each other and to other such measures in the literature, e.g., from Bachmann, Elstner, and Sims (2013). The upper panel of Figure 2.1 plots the cross-sectional mean of $ABSFE^{qual}_{i,\tau}$, i.e., $MEANABSFE^{qual}_{\tau}$, together with the cross-sectional dispersion of expectation errors (see Bachmann, Elstner, and Sims, 2013) defined as

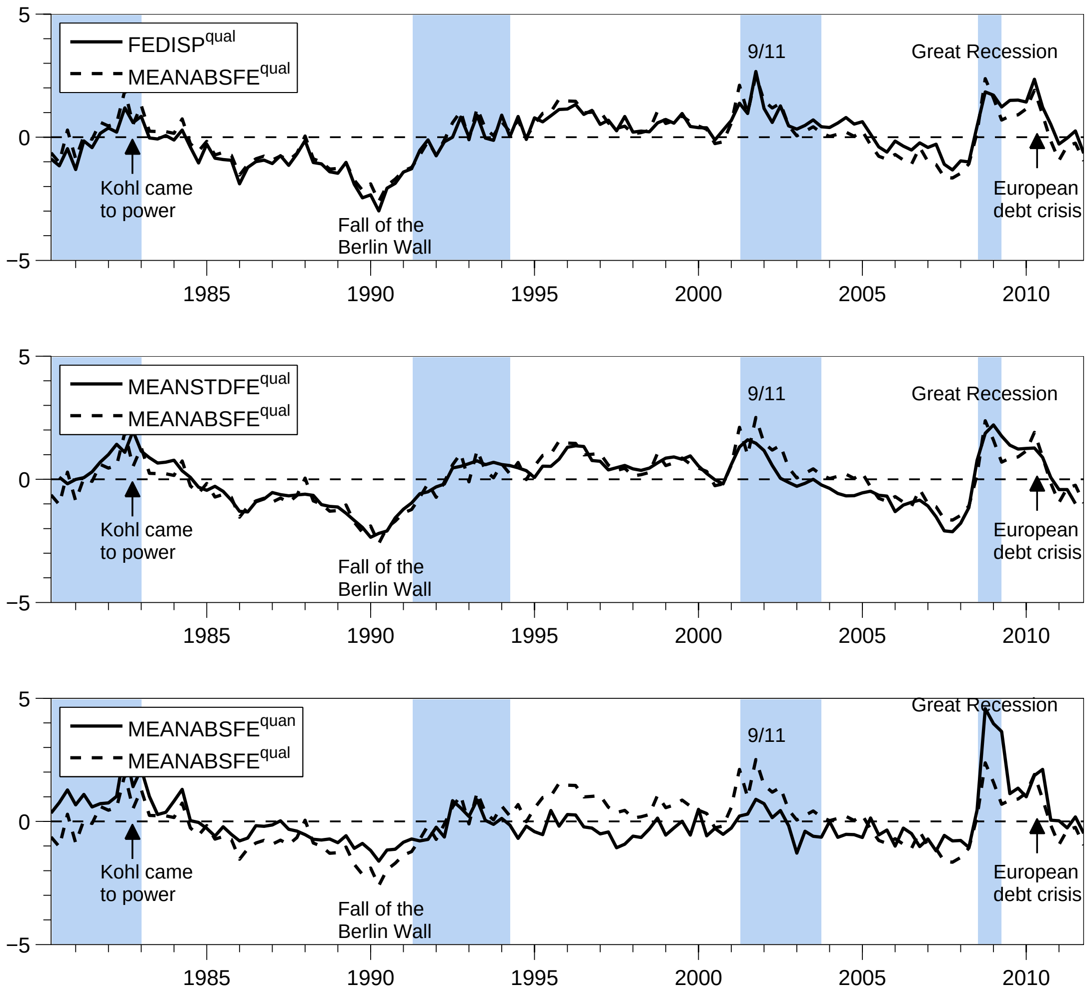
$$FEDISP^{qual}_{\tau} = std\left(FE^{qual}_{i,\tau+3}\right). \tag{2.6}$$

For comparison with the volatility measures based on the *quantitative* forecast errors, we only plot the last month of each quarter for the volatility measures based on the *qualitative* (three-months-ahead) forecast errors, which we have at

end, we classify 71,437 observations as "inconsistent" and drop them. Our final sample consists of 109,721 observations for $\Delta y^{act}_{i,\tau}$.

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

Figure 2.1: Measures of Idiosyncratic Volatility



Notes: The upper panel shows the quarterly time-series of the average absolute ex-post forecast errors, $MEANABSFE_{\tau}^{qual}$ and of the standard deviation of ex-post forecast errors $FEDISP_{\tau}^{qual}$. The middle panel depicts the quarterly time series of the average absolute ex-post forecast errors, $MEANABSFE_{\tau}^{qual}$ and of the average 3-quarter rolling window standard deviation $MEANSTDFE_{\tau}^{qual}$. The lower panel plots the quarterly values of the average absolute ex-post qualitative forecast errors, $MEANABSFE_{\tau}^{qual}$ and the average absolute ex-post quantitative forecast errors, $MEANABSFE_{\tau}^{quan}$. Monthly series are transformed to the quarterly frequency by selecting the last month of each quarter. The sample period is I/1980 - IV/2011. Each series has been demeaned and standardized by its standard deviation. All time series are seasonally adjusted. Shaded regions show recessions as dated by the Economic Cycle Research Institute (ECRI, `www.businesscycle.com`): I/1980 - IV/1982, I/1991 - II/1994, I/2001 - III/2003 and II/2008 - I/2009.

the monthly frequency. The upper panel of Figure 2.1 shows that both time series display similar properties - 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. All in all, we see a close link between both idiosyncratic volatility measures. The visual evidence is supported by the high time-series correlation coefficient of 0.94 between $FEDISP_{\tau}^{qual}$ and $MEANABSFE_{\tau}^{qual}$.

The middle panel of Figure 2.1 shows the cross-sectional mean of $STDFE_{i,\tau}^{qual}$, i.e., $MEANSTDFE_{\tau}^{qual}$, together with $MEANABSFE_{\tau}^{qual}$. 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.[29] The strong comovement between $FEDISP_{\tau}^{qual}$, $MEANABSFE_{\tau}^{qual}$, and $MEANSTDFE_{\tau}^{qual}$ shows that at least in an average sense large absolute forecast errors at the firm-level are not simply the result of mere wrongness of individual firms about their forecasts, but rather the result of heteroskedasticity, i.e., of time-varying distributions.

The link between the qualitative and the quantitative absolute expectation error is illustrated in the lower panel of Figure 2.1 where we plot the cross-sectional mean of $ABSFE_{i,\tau}^{quan}$ ($MEANABSFE_{\tau}^{quan}$) together with $MEANABSFE_{\tau}^{qual}$. Both measures of idiosyncratic volatility 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 also 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 2.4).

Further evidence for the appropriateness of our measures comes from disaggregating the time series and analyzing the time-series correlation coefficients for 13 manufacturing industries and 5 firm-size classes separately. The results are summarized in Table 2.14 in Appendix 2.A. Columns 2 and 3 report correlations for $MEANABSFE_{\tau}^{qual}$ and $FEDISP_{\tau}^{qual}$. All industrial sectors and firm-size

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

Table 2.4: Cross-Correlations

	$FEDISP^{qual}$	$ABSFE^{qual}$	$STDFE^{qual}$	$ABSFE^{quan}$	$STDFE^{quan}$
$\Delta \log Production$	-0.21	-0.26	-0.35	-0.44	-0.25
$\Delta \log Hours$	-0.24	-0.30	-0.37	-0.25	-0.23
$\Delta \log Employment$	-0.41	-0.44	-0.47	-0.26	-0.25
$FEDISP^{qual}$	1.00	0.94	0.83	0.55	0.16
$ABSFE^{qual}$		1.00	0.89	0.62	0.36
$STDFE^{qual}$			1.00	0.69	0.52
$ABSFE^{quan}$				1.00	0.53
$STDFE^{quan}$					1.00

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

classes feature correlation coefficients that are around 0.9 or higher. The last two columns compare $MEANABSFE_{\tau}^{qual}$ and $MEANSTDFE_{\tau}^{qual}$. Here, the strong relationship decreases somewhat at the disaggregate level, however, most correlations are still in the range of 0.6 and 0.8.

2.3 Empirical Analysis

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

2.3.1 Construction of Price Variables

Although the IFO-BCS includes price statements at the monthly frequency, other variables used in this approach such as capacity utilization are only available on a quarterly basis. We therefore estimate a quarterly model as the baseline. Thus, we need to transform the monthly price statements to a quarterly frequency. The quarterly price variable is based on question Q3 from Table 2.1.

Table 2.5: Business Cycle Properties of Frequency of Price Changes

Dependent variable: Share of price change		
	PPI	CPI
Non-Recession Mean	0.3128***	0.4366***
	(0.0054)	(0.0091)
Recession Dummy	0.0271***	0.0459***
	(0.0096)	(0.0158)
Mean of Dep. Var.	0.3215	0.4517
Observations	128	88
Adj. R-squared	0.052	0.078

*** 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 and a recession dummy (with standard errors in parentheses). All data is seasonally adjusted using quarterly dummies. The PPI sample is based on the survey of West-German manufacturing firms and spans the period 1980Q1-2011Q4 while the CPI sample is based on a survey of West-German retail firms and is available for the period 1990Q1-2011Q4. Recessions are as dated by ECRI (see notes to Figure 2.1).

$Price\ change_{i,t}$ 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.[30]

The *PPI* column of Table 2.5 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 somewhat higher in recessions (33.99%) than in normal times (31.28%).

We analyze qualitative price statements of manufacturing firms that are conceptually close to the producer price index (PPI). While the IFO-BCS has data concerning retail firms that would be closer to consumer prices, the 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. Due to data availability in the retail part of the survey, our sample only starts in 1990. Retail firms feature a higher probability to reset their prices: on average 45 percent of all retail firms adjust their prices each quarter compared to 32 percent in manufacturing. The frequency of price adjustment of the retail sector increases in recessions by 4.6 percentage points on average.[31]

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

[31] We report these numbers as a bridge to the results in Vavra (2014) and Berger and Vavra (2011). At the *monthly* frequency, we find for our data that during recessions the frequency

2.3.2 A First Look at the Link between Price-setting Frequency and Business Volatility

Before proceeding with our baseline empirical model, we find it useful to have a first look at the relationship between a firm's price-setting behavior and the idiosyncratic volatility it faces. To this end, we compute for each firm the average frequency of price changes and the average idiosyncratic volatility measured by our volatility proxies. For each of our volatility proxies, we then run a least-squares regression of average frequency of price changes on the average idiosyncratic volatility, where we also include sector-specific dummies. The results presented in Table 2.6 show (with one exception) a significant positive relationship between a firm's average frequency of price change and its average idiosyncratic volatility. In the remainder of this section we investigate whether this positive link is simply the result of averaging or is likely to reflect an underlying relationship of firm-level decision making.

2.3.3 Specification of the Empirical Model

We use a quarterly probit model[32] to estimate the probability of observing a price change, i.e.,

$$P(y_{i,t} = 1 \,|\mathbf{x}_{i,t}) = \Phi(\mathbf{x}_{i,t}\mathbf{b}) \;, \tag{2.7}$$

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.[33]

Table 2.7 lists the variables used in the estimation procedure. At the heart of the empirical analysis are the volatility measures described in detail in Section 2.2. We use two qualitative volatility measures ($ABSFE^{qual}$ and $STDFE^{qual}$) and two quantitative ones ($ABSFE^{quan}$ and $STDFE^{quan}$).[34] Taylor dummies

of price adjustment is 1.6 percentage points higher. This is in line with the findings of Vavra (2014) who finds that during recessions the frequency of price adjustment is 1.2 percentage points higher for U.S. monthly CPI data (see also Berger and Vavra, 2011). He also reports an average monthly price change frequency of 15.0% which corresponds well to our monthly average of 17.6%.

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

[33] As asymmetries might be important in firms' price setting, we also estimate two specifications which separately model the probability of a price increase and a price decrease. We find that heightened volatility leads to a rise in price dispersion, i.e., it increases both the probability of an increase and that of a decrease. Detailed results are presented in Appendix 2.C.

[34] Recall that for the construction of volatility measures based on quantitative expectation errors we had to restrict our sample to firms with constant production expectations. However,

Table 2.6: Average Price-Change Frequency and Average Volatility

Dependent variable: Average frequency of price change of a firm				
	(1)	(2)	(3)	(4)
$ABSFE_i^{qual}$	0.060***			
	(0.006)			
$ABSFE_i^{quan}$		0.127***		
		(0.026)		
$STDFE_i^{qual}$			0.096***	
			(0.008)	
$STDFE_i^{quan}$				0.067
				(0.046)
Observations	8,897	6,894	7,822	3,251
R^2	0.062	0.085	0.084	0.121

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

Notes: The table reports OLS coefficients with standard errors in parentheses. Included in the OLS model but not shown in the table are sector-specific dummies. Each column represents a separate regression employing one of our volatility proxies. Averages are taken for each firm over time. $ABSFE_i^{qual}$: average qualitative idiosyncratic volatility; $ABSFE_i^{quan}$: average quantitative idiosyncratic volatility; $STDFE_i^{qual}$: average 3-quarter rolling window standard deviation of a firm's qualitative expectation errors; $STDFE_i^{quan}$: average 3-quarter rolling window standard deviation of a firm's quantitative expectation errors.

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

One of the advantages of the IFO-BCS 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*

this does not seem to be very restrictive as the correlation of the frequency of price changes between the entire sample and the one based on qualitative expectation errors ($\rho = 0.92$), the entire and the quantitative ($\rho = 0.80$), and the qualitative and the quantitative samples ($\rho = 0.91$) is very high. We also ran the estimation using $ABSFE^{qual}$ on the restricted sample that we use in the regressions with $ABSFE^{quan}$, and the results are robust.

Table 2.7: Description of Variables

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

Capacity, and *Expected Employees*.[35] Changes in input costs are included to capture supply shocks. Lein (2010) emphasizes the important role of intermediate goods costs as a determinant of its price setting. *Orders* are important to account for a possible indirect effect of uncertainty on price setting through demand, insofar this effect is not already captured by the time-fixed effects in the regression, i.e., the possibility that heightened uncertainty may lead to the postponement of projects in other firms, which would decrease the demand for certain goods in the economy.

The qualitative firm-specific variables *Business Situation*, *Business Expectations*, *Orders*, *Technical Capacity*, and *Expected Employees* have three possible response categories (see Table 2.1), e.g., firms can appraise their current state of business as good, satisfactory, or unsatisfactory. To account for possible asym-

[35] 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.

metric effects we include these variables with both positive and negative values separately. For example, the variable *Business Situation* is divided into two sub-variables. If firm i at time t reports its state as good, the variable $Statebus^{+}_{i,t}$ is equal to one, and the variable $Statebus^{-}_{i,t}$ is equal to zero. If the firm answers that its state is unsatisfactory, $Statebus^{+}_{i,t}$ is equal to zero, and $Statebus^{-}_{i,t}$ is equal to one. If the firm believes that its state is satisfactory, both $Statebus^{+}_{i,t}$ and $Statebus^{-}_{i,t}$ are equal to zero, which is the baseline. We proceed analogously with *Business Expectations*, *Orders*, *Technical Capacity*, and *Expected Employees*.

The IFO-BCS contains no direct information about input costs, which is why we construct a variable that proxies the change in the cost of input goods for each sector k for each time period ($\Delta Costs_{k,t}$) following Schenkelberg (2014). $\Delta Costs_{k,t}$ 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.[36]

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).

2.3.4 Baseline Results

The estimation results of the pooled probit benchmark models with *Price change* as the dependent variable are presented in Table 2.8. The first four models – Columns (1) to (4) – include a set of sector, Taylor and time-fixed effects dummies and a constant. The other four models – Columns (5) to (8) – contain, in addition, the set of firm-specific variables described in Table 2.7. Each of the eight models includes one volatility measure. Models (1) and (5) use the absolute qualitative forecast error, $ABSFE^{qual}$, (2) and (6) the absolute quantitative forecast error, $ABSFE^{quan}$, (3) and (7) the 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, $STDFE^{quan}$.

[36] See Appendix 2.B for a detailed description.

Table 2.8: Benchmark Results (Pooled Probit Model) for Price Change

Dependent variable: Price change								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$ABSFE^{qual}$	0.012***				0.008***			
	(0.001)				(0.002)			
$ABSFE^{quan}$		0.097***				0.092***		
		(0.020)				(0.024)		
$STDFE^{qual}$			0.040***				0.019***	
			(0.003)				(0.003)	
$STDFE^{quan}$				0.235***				0.182**
				(0.076)				(0.077)
Capacity utiliz.					0.001***	0.001***	0.001***	0.002***
					(0.000)	(0.000)	(0.000)	(0.000)
Δ Costs					0.224***	0.313***	0.068***	0.168***
					(0.021)	(0.037)	(0.020)	(0.065)
$Statebus^{+}$					0.034***	0.039***	0.028***	0.045***
					(0.004)	(0.006)	(0.004)	(0.011)
$Statebus^{-}$					0.047***	0.064***	0.039***	0.077***
					(0.004)	(0.009)	(0.004)	(0.021)
$Expbus^{+}$					0.018***	0.019**	0.013***	0.027
					(0.004)	(0.008)	(0.004)	(0.018)
$Expbus^{-}$					0.057***	0.040***	0.050***	0.013
					(0.004)	(0.008)	(0.004)	(0.017)
$Orders^{+}$					0.076***	0.064***	0.063***	0.054***
					(0.004)	(0.006)	(0.004)	(0.013)
$Orders^{-}$					0.060***	0.048***	0.048***	0.051***
					(0.004)	(0.006)	(0.004)	(0.012)
Tech. $capacity^{+}$					0.013***		0.010***	
					(0.004)		(0.003)	
Tech. $capacity^{-}$					0.050***		0.040***	
					(0.006)		(0.006)	
$Expempl^{+}$					0.029***		0.022***	
					(0.006)		(0.005)	
$Expempl^{-}$					0.030***		0.025***	
					(0.004)		(0.004)	
Observations	249,363	62,982	231,332	16,239	198,297	55,370	184,756	14,458
Pseudo R-squared	0.121	0.131	0.124	0.162	0.133	0.137	0.134	0.167

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

Notes: The table reports marginal effects. Robust and clustered (by firm) standard errors are in parentheses. Included in the pooled probit model but not shown in the table are time-fixed effects for each quarter, sector-specific dummies, and Taylor dummies. Models (5) and (7) include, in addition, all firm-specific variables described in Table 2.7. 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.

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

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

The takeaway from Table 2.8 for our research question is the following: regardless of the way volatility is measured and regardless of whether firm-specific variables are included, higher volatility increases the probability of a price change. The signs of the marginal effects of $ABSFE^{qual}$ show that higher volatility increases the probability of a price change in both specifications (see Columns (1) and (5)). However, the size of the marginal effects of $ABSFE^{qual}$ is difficult to interpret. In contrast, the marginal effects for $ABSFE^{quan}$ imply that prices are about 0.1 percentage points more likely to change when the corresponding measure of volatility changes by one percentage point. To put this into perspective, in the recent financial crisis we observed that business volatility increased by 7.6 percentage points.

Turning to the rolling window proxies, we find that the marginal effects for $STDFE^{qual}$ are also positive as are the marginal effects for $STDFE^{quan}$. The point estimate for the elasticity is about twice as high as the elasticity for $ABSFE^{quan}$, which, however, is largely explained mechanically by the lower overall variability of $STDFE^{quan}$.

One might argue that our results are potentially driven by first-moment shocks. There are three points that will mitigate this concern. First, including a number of firm-specific variables to control for first-moment effects does not change our results. As can be seen by comparing columns (1) and (2) to columns (5) and (6), the estimation excluding and including firm-specific variables yields similar marginal effects. Second, using the rolling window standard deviation proxy, which has a built-in mean correction, yields similar results to the case with the absolute forecast error as volatility proxy. Third, estimating monthly models separately for price increases and price decreases, we find that heightened volatility increases the probability of both price increases and price decreases (see Appendix 2.C). This increase in price dispersion is exactly what one would expect after a second-moment shock.

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

2.4 Model Evidence

2.4.1 New Keynesian DSGE model

Our empirical results show that an increase in firm-specific volatility leads to an increase in the probability of a price change. To assess the quantitative consequences of this finding for the effectiveness of monetary policy, we use a standard New Keynesian DSGE model (see, e.g., Galí, 2008) where price setting is constrained à la Calvo (1983). The induced price rigidities are the only source of monetary non-neutrality and are captured by the Calvo parameter which fixes the probability of a price change for a given firm. Given the uncovered empirical relationship between an increase in firm-specific volatility and the probability of a price change, we model a change in firm-specific volatility through an unforeseen, permanent and once-and-for-all change in the Calvo parameter. Of course, this mapping between our empirical results and the model is not perfect. We view our simple model exercise as a first-pass, back-of-the-envelope calculation of what the effects of changing firm-level volatility on the effectiveness of monetary policy could quantitatively be. Given that the model is standard, our exposition is kept short.

Households

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

$$U = E_0 \sum_{t=0}^{\infty} \beta^t \left[\frac{C_t^{1-\sigma}}{1-\sigma} - \psi \frac{L_t^{1+\phi}}{1+\phi} \right] \tag{2.8}$$

where $\psi \geq 0$ scales the disutility of labor, σ defines the constant relative risk aversion parameter and ϕ is the inverse of the Frisch elasticity of labor supply.

Given the aggregate price index P_t, the household faces the following budget constraint

$$C_t + \frac{B_t}{P_t} = \frac{W_t}{P_t} L_t + \frac{B_{t-1}}{P_{t-1}} \frac{R_{t-1}}{\pi_t} + \Xi_t \tag{2.9}$$

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 $\pi_t = P_t/P_{t-1}$.

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

$$Y_t = \left[\int_0^1 Y_{it}^{\frac{\epsilon-1}{\epsilon}} di \right]^{\frac{\epsilon}{\epsilon-1}} \tag{2.10}$$

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

$$P_t = \left(\int_0^1 P_{it}^{1-\epsilon} di \right)^{\frac{1}{1-\epsilon}} . \tag{2.11}$$

Intermediate Good Firms

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

$$Y_{it} = A_t L_{it}^{1-\alpha} \tag{2.12}$$

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

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

$$\max \ E_t \sum_{k=0}^{\infty} \theta^k \Lambda_{t,t+k} \left[\frac{P_{it}}{P_{t+k}} - MC_{i,t+k}^r \right] Y_{i,t+k} \tag{2.13}$$

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

Monetary Policy

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

$$\frac{R_t}{\overline{R}} = \left(\frac{\pi_t}{\overline{\pi}}\right)^{\gamma} v_t \tag{2.14}$$

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 $\log v_t = \rho_v \log v_{t-1} + \epsilon^m_t$ where ϵ^m_t is a zero mean white noise process.

Calibration

We calibrate the log-linearized model using standard values from Galí (2008). Table 2.9 presents the calibrated parameter values. The model period is one quarter. The parameter ψ is chosen such that the representative household devotes one third of her time to work. For the experiments following in the next subsection, we use the period prior to the Great Recession, i.e., from 1980Q1 to 2008Q1, to calibrate the steady-state price frequency of the model. In this time span, on average 31.56% of firms adjust their price in a given quarter, corresponding to a Calvo parameter, θ, of 0.6844.

Table 2.9: 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

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

Using this New Keynesian business cycle model, we are now able to conduct a number of experiments to flesh out the connection between firm-level volatility, price flexibility, and the effectiveness of monetary policy. In our baseline economy, a 25 basis point monetary policy shock leads, on impact, to a 0.3465 percent deviation of output from its steady state (solid black line in Figure 2.2), which is in line with the findings of, e.g., Christiano, Eichenbaum, and Evans (2005) and Smets and Wouters (2007). During the 08/09-recession, the average share of firms adjusting their price in a given quarter increased by 7.04 percentage points to 38.6%,[37] translating to a θ of 0.614. In this environment, a 25 basis point monetary policy shock has an impact multiplier of 0.289, i.e., monetary policy loses almost 17% of its effect on output compared to the pre-08/09-recession baseline scenario (dashed red line in Figure 2.2). In other words, had the increase in observed price flexibility been entirely due to increased business volatility, time-varying volatility would indeed be a quantitatively important determinant of the effectiveness of monetary policy.

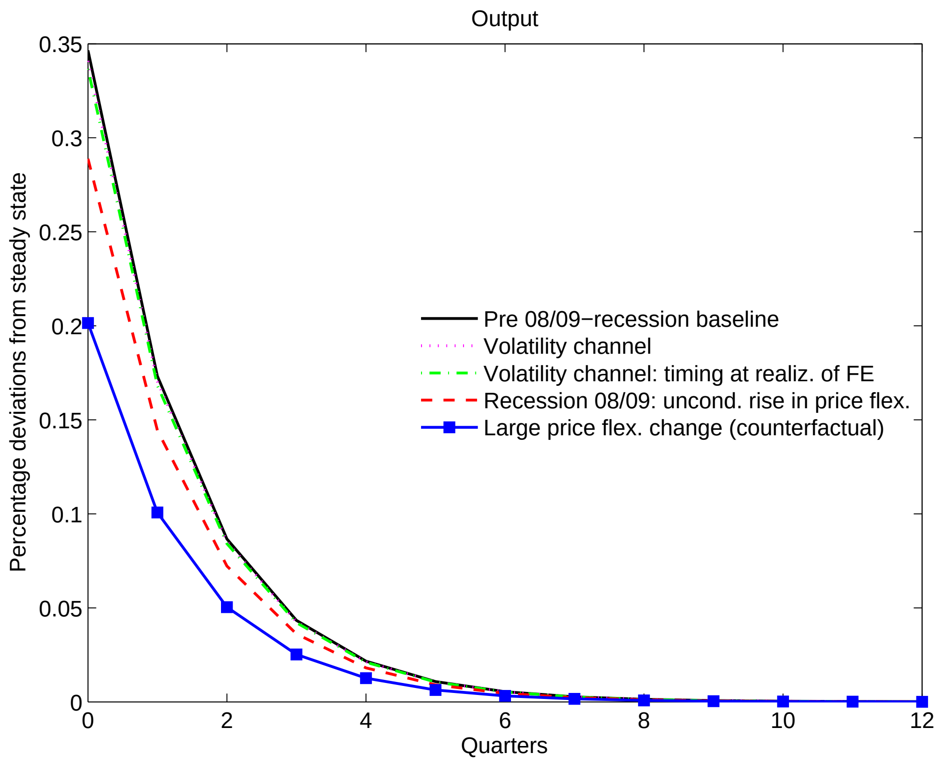
Our microeconometric analysis enables us to quantify how much of this loss in effectiveness is directly attributable to an increase in firm-level volatility. Our quantitative volatility measure, $ABSFE^{quan}$, has a pre-recession sample (1980Q1-2008Q1) mean of 4.7. In the third quarter of 2008, right at the height of the financial crisis, our measure reaches its sample maximum of 12.3, an increase of 7.6 percentage points.[38] We can use our empirical model to compute the change in the probability of a price-adjustment due to this increase in business volatility and translate it into an unforeseen, permanent, and once-and-for-all reduction in the model's Calvo parameter of 0.007.[39] The dotted magenta line in Figure 2.2 shows the response of output in this high-volatility environment to a 25 basis point monetary policy shock. The response is essentially indistin-

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

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

[39] Specifically, we first re-estimate the empirical baseline model on the 1980Q1-2008Q1 sample. We then compute the marginal effects of volatility at the non-recession mean of 4.7 and the 08/09-recession peak of 12.3, thus taking nonlinearities into account. The difference in marginal effects then directly translates into the change of the Calvo parameter. To get an upper bound of the volatility effect, we use the point estimates of the empirical model without firm-specific effects (Column 2 in Table 2.8) for the experiments as they are slightly larger than those with the firm-specific effects included.

Figure 2.2: Impulse Responses to 25 Basis Point Monetary Policy Shock



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

guishable from the response of the baseline model. The impact multiplier is now 0.3409, only 1.6% lower than in the baseline environment. We conclude that it does not appear to be the volatility channel that is at the heart of the increase in price flexibility and the subsequent loss in effectiveness of monetary policy during the 08/09-recession.

In the next section, we will conduct a number of robustness checks. We find the largest overall effect for $ABSFE^{quan}$ on the Calvo parameter for the specification where we change the timing structure such that the realized expectation error is contemporaneous with the pricing decision. This specification maximizes the impact of the volatility effect relative to the "wait-and-see" effect and thus it is no surprise to see this increase in the effect on the frequency of price setting. Repeating the above experiment on the basis of this estimate yields an implied reduction of the Calvo parameter of 0.012. The dash-dotted green line in Figure 2.2 shows the model response for this case. The impact multiplier declines to 0.337, which is 2.9% lower than in the baseline case. This decline still accounts for only one sixth of the unconditional price effect (the 17% loss mentioned above).

We also compute a (counterfactual) scenario where we take the difference between a time of very low price flexibility (1998Q3) and a time when firms were changing prices much more rapidly (2008Q3) and feed this 18 percentage-point change in the Calvo parameter into the model. We use this number to get a rough estimate of the maximum change in monetary non-neutrality over our sample. The resulting impulse response function of output to a 25 basis point monetary policy shock for this case is shown in Figure 2.2 (solid blue line with squares). The impact deviation of output from its steady state is now only 0.2015, almost 42% lower than in our baseline calibration. This number is close to the 55%-loss in the effectiveness of monetary policy that Vavra (2014) finds between times of high and low volatility.

2.5 Robustness Checks

The results of the econometric baseline model show that the probability of price adjustment increases by 0.092 percentage points when business volatility rises by one percentage point as measured by the absolute expectation errors (see the sixth column in the upper panel of Table 2.10). We now conduct a battery of robustness checks for the empirical exercise.

The first robustness check (Table 2.10, middle panel) concerns the timing of the firm-specific volatility measures, especially for $ABSFE^{qual}$ and $ABSFE^{quan}$. The idea behind our baseline timing assumption is that a realized expectation error in quarter $t+1$ means also that a firm was uncertain at the time of expectation formation t. In this robustness check, we change the timing structure such that the realized expectation error is contemporaneous with the pricing decision. This timing assumption is likely to make the volatility effect relatively stronger compared to the wait-and-see effect and indeed for $ABSFE^{qual}$ and $ABSFE^{quan}$ we find marginal effects that are twice as large as those of the baseline model.

The second robustness check (Table 2.10, 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 2.1).[40] Thus, in this exercise, we focus on price changes that are unexpected and see whether they react to idiosyncratic volatility. With a value of 0.068, the marginal effect of $ABSFE^{quan}$ is somewhat smaller than that in the baseline model.

We also check whether our estimated coefficients differ between recession and non-recession times. This is not the case as Table 2.11 shows. [41]

For the construction of the quantitative volatility measures, we imposed a number of restrictions on our sample. First, we only looked at firms that had constant production expectations in order to capture production expectation errors. Since our baseline results show that the volatility effect dominates empirically, we also check whether we get the same results if we focus on production changes as opposed to production expectation errors, thus eliminating pure uncertainty effects. Table 2.12 (upper panel) says yes. If, in addition, we relax the assumption of constant potential output, i.e., we now simply base our volatility measures on utilization changes, the results are still robust (see Table 2.12, middle panel). Finally, we do a similar exercise for the volatility measures based on qualitative production expectation errors (see Table 2.12, lower panel). To be specific, we use $REALIZ_{i,t}$ instead of $FE^{qual}_{i,t}$ in Equation 2.1. Our results remain essentially unchanged.

One might be concerned that measurement error contaminates our production forecast error measures. To deal with this problem, we use the so-called control function approach (see Rivers and Vuong, 1988, Wooldridge, 2002, Imbens and Wooldridge, 2007), a two-stage instrumental variable procedure that can also be applied to nonlinear models. In the first stage we regress each forecast error type on the level of capacity utilization, the change of input costs, two dummies for the business situation, two dummies for the change of orders (see Table 2.7),[42] plus Taylor and sector dummies, and time-fixed effects. Since

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

[41] We also run our baseline regression year by year and find mostly positive marginal effects which show no clear cyclical pattern.

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

firms by definition do not react to measurement error, the idea behind this first stage is to extract that component of the measured forecast error to which firms react with observable actions and thus the true forecast error. In the second stage we estimate our baseline probit model which includes our volatility measures on the right hand side (plus Taylor and sector dummies and time-fixed effects), and the residual from the first stage regression as an additional control variable. Including the residual from the first stage directly controls for any potential endogeneity in our volatility measures. The results are essentially unchanged (see Panel (a) of Table 2.13). Also, the second-stage coefficient of the first-stage residual is statistically not distinguishable from zero, which means that endogeneity issues do not appear to be a problem.

In the next exercise we increase the rolling window from 3 to 5 quarters to diminish further the potential problem of capturing first moment shocks by the proxies. The estimation results are shown in Panel (b) of Table 2.13. The coefficient on $STDFE^{quan}$ is now statistically insignificant, though essentially unchanged in terms of the magnitude of the point estimates. This is likely due to the fact that the number of observations decreases for $STDFE^{quan}$ from 14,458 to 6,239 for the model specification including all firm-specific variables.

The final two robustness checks only concern the qualitative measures of volatility, $ABSFE^{qual}$ and $STDFE^{qual}$. Unlike for the volatility measures based on quantitative expectation errors, there is nothing that prevents us from computing these volatility measures at a monthly frequency. Hence, we redo our baseline estimations also for the monthly frequency with basically unchanged results (see Panel (c) of Table 2.13).[43] In the last exercise, we construct a binary firm-level volatility measure that just takes the value one at time t if there is a realized expectation error in $t + 1$. Again, our results remain the same (see Panel (d) of Table 2.13).

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

Table 2.10: Robustness I

Dependent variable: Price change								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Baseline results (pooled probit model)				
ABSFE^{qual}	0.012***				0.008***			
	(0.001)				(0.002)			
ABSFE^{quan}		0.097***				0.092***		
		(0.020)				(0.024)		
STDFE^{qual}			0.040***				0.019***	
			(0.003)				(0.003)	
STDFE^{quan}				0.235***				0.182**
				(0.076)				(0.077)
				Volatility proxy at time of realization (pooled probit model)				
ABSFE^{qual}	0.022***				0.008***			
	(0.001)				(0.001)			
ABSFE^{quan}		0.187***				0.111***		
		(0.021)				(0.020)		
STDFE^{qual}			0.017***				0.006***	
			(0.002)				(0.001)	
STDFE^{quan}				0.031				0.006
				(0.019)				(0.012)
				Unexpected price changes (pooled probit model)				
ABSFE^{qual}	0.008***				0.005***			
	(0.001)				(0.001)			
ABSFE^{quan}		0.083***				0.068***		
		(0.015)				(0.016)		
STDFE^{qual}			0.028***				0.019***	
			(0.002)				(0.002)	
STDFE^{quan}				0.218***				0.202***
				(0.064)				(0.072)

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

Notes: The table presents marginal effects. Robust and clustered (by firm) standard errors are in parentheses. First panel: baseline results; second panel: alternative timing where realized expectation error is contemporaneous with the pricing decision; third panel: we only consider price changes that are putatively unexpected. Included in all models but not shown in the table are time-fixed effects for each quarter, sector-specific dummies, and Taylor dummies. Models (5) and (7) include, in addition, all firm-specific variables described in Table 2.7. 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.

Table 2.11: Robustness Checks II: Sample-Split into Non-Recession and Recession Samples

Dependent variable: Price change

	Non-recession				Recession			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
$\text{ABSFE}^{\text{qual}}$	0.009***		0.004***		0.010***		0.005**	
	(0.001)		(0.001)		(0.002)		(0.003)	
$\text{ABSFE}^{\text{quan}}$		0.063***		0.047***		0.078**		0.064
		(0.015)		(0.014)		(0.032)		(0.041)
$\text{STDFE}^{\text{qual}}$	0.028***		0.012***		0.045***		0.023***	
	(0.003)		(0.002)		(0.004)		(0.004)	
$\text{STDFE}^{\text{quan}}$		0.228***		0.148**		0.120		0.106
		(0.077)		(0.069)		(0.137)		(0.136)

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

Notes: The table reports marginal effects. Robust and clustered (by firm) standard errors are in parentheses. Included in the pooled probit model but not shown in the table are time-fixed effects for each quarter, sector-specific dummies, and Taylor dummies. Models (3)-(4) include, in addition, all firm-specific variables described in Table 2.7, 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 2.12: Robustness Checks III

Dependent variable: Price change				
	(1)	(2)	(3)	(4)
	Volatility based on production changes			
ABS^{quan}	0.100***		0.095***	
	(0.017)		(0.021)	
STD^{quan}		0.151***		0.108**
		(0.049)		(0.053)
	Volatility based on capacity utilization changes			
ABS^{quan}	0.120***		0.101***	
	(0.010)		(0.012)	
STD^{quan}		0.211***		0.154***
		(0.018)		(0.019)
	Qualitative production change			
ABS^{qual}	0.028***		0.016***	
	(0.001)		(0.002)	
STD^{qual}		0.049***		0.022***
		(0.003)		(0.003)

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

Notes: The table presents marginal effects. All estimations are based on the pooled probit model. First panel: volatility measure based on production changes as opposed to production expectation errors; second panel: volatility measure based on capacity utilization changes; third panel: qualitative production realization as volatility measure (i.e., $REALIZ_{i,t}$ replaces $FE_{i,t}^{qual}$ in Equation 2.1). Robust and clustered (by firm) standard errors are in parentheses. Included in all models but not shown in the table are time-fixed effects for each quarter, sector-specific dummies, and Taylor dummies. Models (3) and (4) include, in addition, all firm-specific variables described in Table 2.7, except *Technical Capacity* and *Expected Employees* in the specification of the first panel.

Table 2.13: Robustness Checks IV

Dependent variable: Price change				
	(1)	(2)	(3)	(4)
	(a) Control function approach			
$\text{ABSFE}^{\text{qual}}$	0.012***		–	
	(0.002)			
$\text{ABSFE}^{\text{quan}}$		0.099***		–
		(0.024)		
	(b) 5-quarter rolling window standard deviation			
$\text{STDFE}^{\text{qual}}$	0.035***		0.016***	
	(0.003)		(0.002)	
$\text{STDFE}^{\text{quan}}$		0.191		0.032
		(0.132)		(0.132)
	(c) Monthly model			
$\text{ABSFE}^{\text{qual}}$	0.004***		0.002**	
	(0.001)		(0.001)	
$\text{STDFE}^{\text{qual}}$		0.012***		0.004***
		(0.001)		(0.001)
	(d) Volatility measure as dummy variable			
$\text{ABSFE}^{\text{qual}}$	0.017***		0.010***	
	(0.002)		(0.003)	

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

Notes: The table presents marginal effects. All estimations are based on the pooled probit model. First panel: control function approach where the second stage includes time-fixed effects, sector dummies, Taylor dummies, and the residual of the first stage; second panel: 5-quarter rolling window instead of the baseline 3-quarter one; third panel: volatility measure computed from monthly three-month-ahead qualitative production forecast errors; fourth panel: binary volatility measure that takes the value one at time t if there is a realized expectation error in $t+1$. Robust and clustered (by firm) standard errors are in parentheses. Included in the pooled probit model but not shown in the table are time-fixed effects, sector-specific dummies, and Taylor dummies. Models (3) and (4) include, in addition, all firm-specific variables described in Table 2.7 except *Capacity Utilization*, *Technical Capacity* and *Expected Employees* for the monthly model which are all at a quarterly frequency and except *Technical Capacity* and *Expected Employees* for the quantitative models. Taylor dummies in the monthly model are defined with respect to the last *month* in which a firm resets its price, e.g., $Taylor2$ takes a value of one if the last time a firm adjusted its price was two months ago. As in the quarterly specifications, we include two years worth of Taylor dummies.

2.6 Conclusion

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

This last point is particulary important for economic decision makers. Recent evidence points to volatility/uncertainty playing a role in the decision-making process of central bankers (e.g., Jovanovic and Zimmermann, 2010, Bekaert, Hoerova, and Lo Duca, 2013, Kohlhas, 2011). Our analysis, however, indicates that the role of heightened volatility (and of uncertainty) might be of minor concern for the conduct of traditional monetary policy. Of course, the monetary policy part of our analysis is somewhat dependent on the specific model environment that we chose to translate predicted changes in the frequency of price changes due to heightened firm-level volatility into price flexibility (or lack thereof) in the model, but at the very least our empirical estimates provide a new elasticity between volatility and price change frequency that any model of price setting should satisfy in order to speak quantitatively about the link between volatility and the effectiveness of monetary policy. Also, our analysis is mute on issues like the interaction of volatility/uncertainty with financial frictions, a channel a growing recent literature has emphasized, and which might become more important as monetary policy is viewed as increasingly responsible for ensuring financial stability. More generally, it seems important to understand why price rigidities seem to change so significantly over the business cycle and which consequences for monetary policy these fluctuations in the extensive margin of price setting might have.

Appendix

2.A Link between $MEANABSFE$, $MEANSTDFE$, and $FEDISP$

Table 2.14: Time Series Correlation Coefficients between $MEANSTDFE_{\tau}^{qual}$, $MEANABSFE_{\tau}^{qual}$, and $FEDISP_{\tau}^{qual}$

	Correlation between $MEANABSFE_{\tau}^{qual}$ and $FEDISP_{t}^{qual}$		Correlation between $MEANABSFE_{\tau}^{qual}$ and $MEANSTDFE_{\tau}^{qual}$	
Group of Firms	raw data	seasonally adjusted	raw data	seasonally adjusted
Manufacturing	0.93	0.94	0.89	0.90
Industry				
Transport Equipment	0.92	0.90	0.67	0.69
Machinery and Equipment	0.94	0.94	0.81	0.81
Metal Products	0.92	0.92	0.77	0.78
Other non-metallic Products	0.90	0.90	0.65	0.69
Rubber and Plastic	0.85	0.85	0.63	0.67
Chemical Products	0.88	0.89	0.59	0.62
Elect. and Opt. Equipment	0.95	0.95	0.75	0.78
Paper and Publishing	0.91	0.91	0.81	0.81
Furniture and Jewelery	0.89	0.90	0.49	0.53
Cork and Wood Products	0.93	0.93	0.68	0.74
Leather	0.91	0.91	0.53	0.60
Textile Products	0.93	0.93	0.67	0.68
Food and Tobacco	0.89	0.88	0.74	0.78
Firm Size				
less than 50 employees	0.94	0.94	0.79	0.78
between 50 and 199 employees	0.93	0.92	0.80	0.87
between 200 and 499 employees	0.94	0.94	0.77	0.79
between 500 and 999 employees	0.94	0.95	0.73	0.75
more than 999	0.94	0.94	0.73	0.74

Notes: This table provides in the first two columns time-series correlation coefficients between $MEANABSFE_{\tau}^{qual}$ 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 $MEANABSFE_{\tau}^{qual}$ and $MEANSTDFE_{\tau}^{qual}$. 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 $MEANABSFE_{\tau}^{qual}$, $FEDISP_{t}^{qual}$, and $MEANSTDFE_{\tau}^{qual}$ is explained in Section 2.2.

2.B Description of the Input Cost Variable

To compute a proxy for the cost of input goods, $\text{Costs}_{k,t}$ in sector k, we follow the approach outlined in Schenkelberg (2014). In this approach, a weighted price variable of all sectors K that provide input goods for each production sector k is computed. This procedure follows three steps. First, we compute the weights of inputs for each sector k. To this end, we use data from input-output tables from the German Statistical Office. This data provides for each sector k the cost of input goods from each sector l (including from its own sector). Data is available for the years 1995 to 2007. For each year we calculate the cost share of the respective sector l used in the production process of sector k. Finally, we average these shares across time. Second, from the IFO-BCS we know whether a firm i from sector l changes its price in period t. We compute the net balance of price changes within a given sector l for each period t. That is, we subtract all price decrease from all price increases. We, therefore, need to assume that price increases (decreases) are similar across different firms within a sector. This gives us a proxy of the price of input goods from sector l. Third, we combine the weights of input goods from sector l in the production in sector k (from step one) with the respective price of goods from sector l at period t (from step two). The resulting time series is a proxy for input costs which sector k faces for each time period t.

To check our procedure we calculate a different proxy for input costs based on producer prices, $\text{Costs}_{k,t}^{ppi}$, which the German Federal Statistical Office publishes for all sectors. The problem with this in principle superior measure is that the data are only consistently available since 1995 on. We proceed as above. We compute the quarterly inflation rates of the producer prices for each sector k. We combine the weights of input goods form sector l in the production process in sector k with the respective producer prices inflation rate from sector l. We get a time series of input costs for each sector k for each time period. Time series correlation coefficients between $\text{Costs}_{k,t}$ and $\text{Costs}_{k,t}^{ppi}$ for the period of overlap are shown in Table 2.15. 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 2.15: 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.

2.C Asymmetric Price Responses

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

We then estimate probit models in the spirit of the estimations in the main part of the paper, with the corresponding price increase and price decrease variables as dependent variables. We focus on $ABSFE^{qual}$ and $STDFE^{qual}$ as only these volatility measures are available at the monthly frequency. We use a specification at the monthly frequency because this makes the definition of a price increase and a price decrease unambiguous. The results are presented in Table 2.16. Heightened volatility increases the probability of both price increases and price decreases. This is another indication that the volatility effect dominates the wait-and-see effect. That is, price changes are more dispersed in times of higher volatility.

Table 2.16: Pooled Probit Model with Price Increase/Decrease (Monthly Model)

	(1)	(2)	(3)	(4)
Dependent variable: Price increase				
$\text{ABSFE}^{\text{qual}}$	0.002		0.002***	
	(0.001)		(0.001)	
$\text{STDFE}^{\text{qual}}$		0.001		0.002
		(0.002)		(0.001)
Dependent variable: Price decrease				
$\text{ABSFE}^{\text{qual}}$	0.001***		0.001***	
	(0.000)		(0.000)	
$\text{STDFE}^{\text{qual}}$		0.002***		0.002***
		(0.000)		(0.001)
Observations	756,814	695,782	750,623	203,222

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

Notes: The table presents marginal effects. Robust and clustered (by firm) standard errors are in parentheses. Included in the pooled probit model but not shown in the table are time-fixed effects for each month, sector-specific dummies, and Taylor dummies. Models (3)-(4) include, in addition, all firm-specific variables described in table 2.7. Taylor dummies are defined with respect to the last *month* in which a firm resets its price, e.g., $Taylor2$ takes a value of one if the last time a firm adjusted its price was two months ago. As in the quarterly specifications, we include two years worth of Taylor dummies. $ABSFE^{qual}$: qualitative idiosyncratic volatility; $STDFE^{qual}$: 3-quarter rolling window standard deviation of a firm's qualitative expectation errors.

CHAPTER 3

Uncertainty Shocks and Credit Spreads in Bank-Based and Market-Based Financial Systems

This paper takes an empirical and theoretical look at the relationship between uncertainty and credit spreads. Innovations in uncertainty increase credit spreads; we confirm this result from the literature for spreads on corporate bonds both for the United States and for Germany. In contrast, credit spreads on bank loans increase much less. Decomposing these two type of spreads, we document a new stylized fact: following a sudden increase in uncertainty, corporate bond yields increase, whereas bank loan rates decrease. We show that a New Keynesian dynamic stochastic general equilibrium model with costly state verification produces increasing lending rates in response to surprise increases in uncertainty. Therefore, this model replicates the dynamics in corporate bond markets. By introducing relationship lending into a partial equilibrium model with costly state verification, we show that bank loan rates are comparatively lower in a high-uncertainty environment.

3.1 Introduction

A recent strand of the literature on uncertainty argues that financial frictions are a channel through which uncertainty affects the real economy. Gilchrist, Sim, and Zakrajsek (2014) and Christiano, Motto, and Rostagno (2014) suggest that higher uncertainty about idiosyncratic productivity increases the probability of firm default, which in turn raises the risk premium on firm loans. As it becomes more expensive to take on loans, investment drops and so does output.[44] Gilchrist, Sim, and Zakrajsek (2014) present empirical support for the United States using corporate bond yields as measure for the cost of external financing. However, firms in the Euro Area rely heavily on banks for financing instead of on the capital market.[45] The relationship between firms and banks is different (compared to that between firms and the capital market) because banks are able to form long-term relationships with their borrowers (see, e.g., Boot, 2000, Boot and Thakor, 2010, Diamond, 1984, Petersen and Rajan, 1994, Sharpe, 1990). To preserve these relationships, banks smooth loan rates over the business cycle to protect firms from fluctuations in market rates (Berger and Udell, 1992).[46]

The paper makes four contributions to the field. First, using uncertainty proxies calculated from survey data, we empirically confirm the result of Gilchrist, Sim, and Zakrajsek (2014) that credit spreads on corporate bonds increase in response to surprise increases in uncertainty, both for the United States and for Germany. In contrast, credit spreads on bank loans increase much less in Germany and do not increase at all in the United States. Second, decomposing these two type of spreads, we document a new stylized fact: following a sudden increase in uncertainty, corporate bond yields increase, whereas bank loan rates decrease. This explains why spreads on corporate bonds increase more than do spreads on bank loans. Third, we show in a dynamic stochastic general equilib-

[44] Other studies that look at the relationship between uncertainty and different types of financial frictions include Arellano, Bai, and Kehoe (2012), Bonciani and van Roye (2013), Chugh (2014), Dorofeenko, Lee, and Salyer (2008), Fendoglu (2014), Fernández-Villaverde (2010), Grimme and Siemsen (2014), and Hafstead and Smith (2012).

[45] Comparing the liability side of U.S. and German nonfinancial firms (using Germany as an example of a country in the Euro Area), the following results emerge. For U.S. firms, corporate bonds make up about 20% of their liabilities compared to 3% in Germany. In contrast, (bank) loans cover about 4% of U.S. firm liabilities whereas in Germany the corresponding number is almost 30%. Figure 3.12 in the Appendix presents the liability side of nonfinancial corporations in the United States and in Germany. De Fiore and Uhlig (2011) find that the ratio of bank loans to debt securities is around eight times larger in the Euro Area than in the United States.

[46] Sticky loan rates in the context of monetary policy are discussed by Gerali, Neri, luca Sessa, and Signoretti (2010), Güntner (2011), Hülsewig, Mayer, and Wollmershäuser (2009), and Scharler (2008).

rium (DSGE) model with costly state verification (CSV), a model extensively used in the literature on uncertainty and financial frictions, that lending rates increase after an uncertainty shock. Therefore, this theoretical model replicates the empirical fact of increasing corporate bond yields but not that of decreasing loan rates. Fourth, we implement in a simple partial equilibrium model with CSV the notion of relationship banking and demonstrate that this model predicts that bank loan rates are relatively lower than lending rates on the capital market in times of uncertainty. Therefore, this model suggests that relationship lending could be an explanation for the different behavior of corporate bond yields and bank loan rates in response to uncertainty shocks.

In the empirical part of the paper, we rely on vector autoregressions (VARs) to analyze the relationship between uncertainty and credit spreads in the United States and Germany. To construct idiosyncratic uncertainty measures, we follow the strategy of Bachmann, Elstner, and Sims (2013) and use survey data from the Philadelphia Fed's Business Outlook Survey (BOS) for the United States and from the IFO Business Climate Survey (IFO-BCS) for Germany. This is in contrast to Gilchrist, Sim, and Zakrajsek (2014), who use U.S. financial data.[47] The drawback of financial data is that it limits the analysis to large firms, whereas survey data encompass firms of all sizes – at least, in the IFO-BCS. Furthermore, survey data capture the mood of actual decision-makers at the firms in contrast to, for example, financial analysts (Bachmann, Elstner, and Sims, 2013). From the survey data, we calculate the cross-sectional dispersion of expectations about future business activity for each country and use it as a proxy for idiosyncratic uncertainty, respectively. We examine the effect of shocks to uncertainty on two types of credit spreads: the spread on corporate bonds which is the difference between corporate bond yields and government bond yields and the spread on bank loans which is the difference between bank loan rates and government bond yields.

A robust result we find is that an increase in uncertainty increases corporate bond spreads more than bank loan spreads. This phenomenon is due to the fact that corporate bond yields increase and bank loan rates decrease. These results are found both for the United States and Germany. The United States can

[47] To derive a measure for idiosyncratic uncertainty, Gilchrist, Sim, and Zakrajsek (2014) use daily stock returns for U.S. nonfinancial corporations. In a first step, they remove the forecastable variation in idiosyncratic excess returns. In a second step, they compute the quarterly firm-level standard deviation of the estimated residuals from the first step. In a third step, it is assumed that this standard deviation follows an AR1 process with firm fixed effects, a firm-specific term and time fixed effects. The series of time fixed effects is used as an aggregate proxy for idiosyncratic uncertainty.

be characterized as a market-bases financial system because U.S. firms borrow heavily from capital markets. In contrast, banks are the primary lenders to German firms. Therefore, the corporate bond spread is a good proxy for the financial conditions in the United States; bank loan spreads better proxy the tightness of financial conditions in Germany. From this it follows, that after a sudden increase in uncertainty, firms in market-based systems are hit harder than in bank-based systems with respect to their financing costs.

The theoretical section of the paper consists of two parts: first, we check whether a DSGE model, which incorporates a CSV problem à la Bernanke, Gertler, and Gilchrist (1999) and an uncertainty process along the lines of Fernández-Villaverde (2010), produces increasing or decreasing lending rates after an innovation in uncertainty. We employ two calibration strategies. First, we calibrate the model to German data and use the IFO-BCS data for calibration of the uncertainty process. Second, we use a sensible range for each of the parameter values so as to include different combinations of parameter values found in the uncertainty literature. Under both strategies, we find that the model supports the capital market story: increasing lending rates follow hikes in uncertainty. In response to an uncertainty shock, capital market participants are compensated for the increased default probability by demanding a higher risk premium.

In contrast, the empirical results suggest that banks reduce loan rates in times of uncertainty and, therefore, are not sufficiently compensated for the increased default risk; bank profits are temporarily reduced. We formulate a stylized partial equilibrium model with CSV that includes the possibility for banks to form relationships with their borrowers. Banks are better at acquiring disclosed information about firms than the capital market (see, e.g., Boot and Thakor, 2010). Reducing these informational asymmetries ties the bank and their borrowers closer together, a lending relationship is formed. In contrast, capital markets rely on publicly available information about the firm (Fama, 1985), each market participant is atomistic, has smaller stakes in the firms and is less specialized in monitoring the borrower (Boot, 2000). Therefore, the capital market is denied the possibility to form lending relationships with firms in our model.

In the partial equilibrium model, we assume an asymmetric information problem in the spirit of Townsend (1979): lenders cannot costlessly observe the payoff of borrowers' investment projects. Thus, banks have an incentive to form relationships with borrowers in order to facilitate monitoring and attenuate the problem of asymmetric information between lenders and borrowers. Having formed a lending relationship, the bank faces lower monitoring costs, which make a firm's default less costly for the bank. Therefore, the bank can charge relatively high lending rates compared to the capital market. If the reduction in expected monitoring costs is sufficiently large, the relationship bank has an incentive to offer relatively low lending rates in periods of high uncertainty. A low rate counteracts the increase in the probability of borrower default due to uncertainty, which, in turn, makes it more likely that the bank can exploit the borrower in the future (after uncertainty vanished) by demanding comparatively high rates. The larger the expected reduction in asymmetries due to the relationship, that is, the larger the future benefits from establishing a relationship, the lower is the bank loan rate relative to the lending rate on the capital market during the uncertainty event.

Section 2 presents the construction of the idiosyncratic uncertainty proxies and describes the measures for credit spreads. Section 3 empirically investigates the effects of uncertainty shocks on credit spreads, corporate bond yields, and bank loan rates; robustness tests are also presented. In the first part of Section 4, we present results from the DSGE model with CSV; the second part introduces the partial equilibrium model. Section 5 concludes.

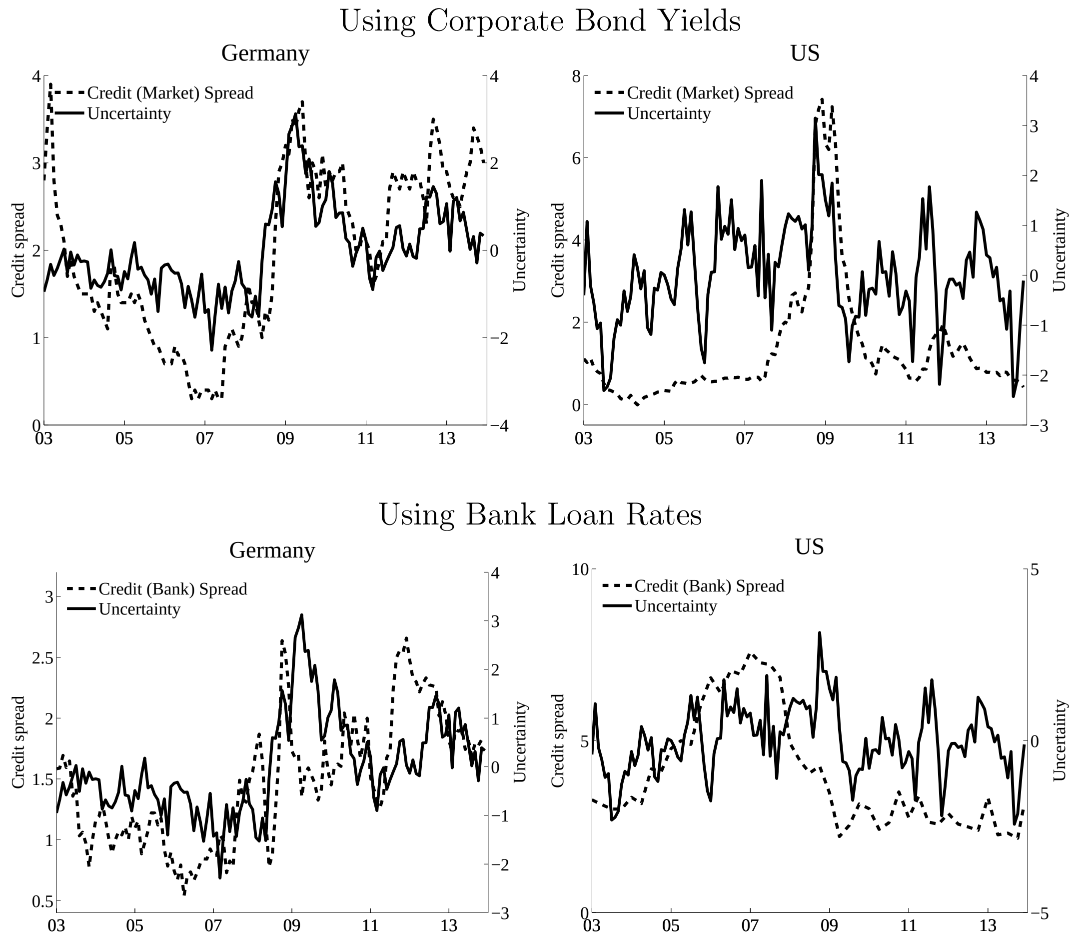
3.2 Measuring Uncertainty and Credit Spreads

This section presents the construction of the idiosyncratic uncertainty proxies and describes the measures for credit spreads.

We follow Bachmann, Elstner, and Sims (2013) in constructing the idiosyncratic uncertainty proxies for Germany and the United States. For Germany, we rely on the responses from manufacturing firms to the IFO-BCS, which is conducted on a monthly basis. The uncertainty proxy $FDISP^{GER}$ is calculated as the cross-sectional dispersion of expectations about future production.[48] For the United States, we use data from the BOS, which is conducted monthly by the Federal Reserve Bank of Philadelphia. The uncertainty proxy $FDISP^{US}$ is calculated as the dispersion of firms' forecasts about the general business outlook. Bachmann, Elstner, and Sims (2013) treat $FDISP^{GER}$ and $FDISP^{US}$ as proxies for idiosyncratic uncertainty for Germany and the United States, respectively.

[48] A more detailed description of the proxies is presented in Appendix 3.A.

Figure 3.1: Uncertainty and Credit Spread



Notes: All series are at a monthly frequency. The uncertainty proxy for Germany, $FDISP^{GER}$, is obtained from the IFO-BCS; that for the United States, $FDISP^{US}$, is from the BOS. Both uncertainty proxies are standardized. For Germany, the credit (market) spread is the difference between the corporate bond yield from outstanding bonds and the one-year government bond yield; for the United States, it is the difference between the three-year investment grade rated corporate bond yield and the three-year treasury bond yield. The (bank) spread for Germany is the difference between the one-year loan rate of new loans to non-financial corporations and the one-year government bond yield; for the United States, it is the difference between the prime rate charged by banks and the three-year treasury bond yield.

For both countries, we compute two credit spreads, respectively. The first type of spread is derived from corporate bond yields. For Germany, we rely on yields from outstanding bonds issued by German nonfinancial corporations. These include securities with a maturity of more than four years, the yields of the individual securities are weighted by the amounts outstanding at market prices. To our knowledge other indexes are not available because of the relatively small market for German corporate bonds. As riskless rate, we use the German government bond yield with a maturity of one year. This means that we face some bias in the spread due to a maturity mismatch (Gilchrist, Sim, and Zakrajsek, 2014), but it allows us to be consistent with the spread on bank loans.[49] The second type of spread is calculated from bank loan rates. For Germany, we use the loan rate of new loans to nonfinancial corporations in Germany with a maturity of one year.[50] This series is part of the MFI interest rate statistics and is collected monthly by the Deutsche Bundesbank from a representative sample of 200-240 banks in Germany. The reported interest rates are weighted with the respective volume of new business loans, which are also reported by the banks, to form an average interest rate. Loans with a maturity of one year cover around 82% of all new loans to nonfinancial corporations. Using only loans with a one-year maturity allows for a consistent comparison with a government bond yield of the same maturity. The rest of new loans either have a maturity of one to five years or a maturity longer than five years. In 2003, the national interest rate statistics of all countries in the Eurozone were harmonized. The difference in the methodology of figuring the interest rate statistics before and after 2003 makes it difficult to compare the loan rates (see Bundesbank, 2004); therefore, this paper only looks at the time period since 2003.

For the United States, we use the corporate bond yield for maturities between one and three years for the calculation of the first type of spread. The yield tracks the performance of outstanding bonds issued by investment grade U.S. corporations. As the corresponding riskless rate, we rely on the government bond yield with a one-year maturity.[51] For the second type of spread, we take the prime rate charged by banks. This rate is the rate charged by the majority of the largest 25 U.S. commercial banks on many of their (short-term) commercial loans and is an indicator for many other loan rates. This is the only loan rate available at a monthly frequency. A drawback of the prime rate is that it is the rate banks charge their most creditworthy borrowers. However, the prime rate and the quarterly loan rate of all commercial and industrial loans with a

[49] Results remain robust with respect to using government bond yields with a maturity of either 4 years, 5 years or 10 years.

[50] In the robustness section we show that the results do not change if we use the loan rate of *outstanding* loans to nonfinancial corporations in Germany with a maturity of one year. To our knowledge, for the United States, only loan rates of *new* loans are available, therefore we use loan rates of new loans throughout the baseline.

[51] Alternatively, we use government bond yields with a three-year maturity. The results are quantitatively similar.

maturity of up to one year from the Survey of Terms of Business Lending are highly correlated; the correlation coefficient is 0.99.

The upper two panels of Figure 3.1 show the uncertainty proxy and the corporate bond credit spread – that is, the difference between the corporate bond yield and the government bond yield – for Germany and the United States for the time period 2003-2013. In each country uncertainty and the market spread co-move; for Germany the correlation coefficient is 0.74, for the United States it is 0.40.

The lower two panels of Figure 3.1 plot the uncertainty proxy and the bank loan credit spread – that is, the difference between the bank loan rate and the government bond yield – for Germany and the United States. Uncertainty and the bank spread co-move in both countries, respectively; the correlation coefficient is 0.49 for Germany; for the United States it is 0.26.

3.3 Empirical Evidence

To analyze how credit spreads respond to surprise increases in uncertainty, we use standard vector autoregressions (VARs). We take data both for the United States and Germany to discover whether the responses differ between economies characterized by firms relying heavily on capital market financing (United States) and bank-based financing (Germany).

3.3.1 Baseline Results

The baseline VARs consist of three variables: a proxy for uncertainty, a measure for the cost of external finance and the government bond yield. The cost of external finance is either the corporate bond yield or the bank loan rate. The sample period is from 2003:M1 to 2013:M12. As mentioned in the previous section, interest rates in the Eurozone before 2003 are conceptually different from those after 2003, which is why the sample starts in 2003. We use the same sample period for the United States so as to make the analysis consistent. The VARs are at a monthly frequency and estimated with a constant and three lags.[52] Uncertainty is ordered before the interest rate variables in a recursive identification.

[52] In the baseline estimations the BIC and the AIC criterion suggest 1 lag for Germany; for the United States the BIC criterion finds 2 lags to be optimal, the AIC criterion finds 3 lags. Estimating the Baseline-VARs with either 6 or 12 lags does not change the qualitative results. In the robustness section, variables are added to the baseline VARs; to keep the estimation feasible due to the relatively short sample period, we use 3 lags throughout the paper if not stated otherwise.

Innovations in uncertainty, therefore, have an immediate impact on the interest rate variables.[53] The government bond yield is ordered before the cost of external finance. In the following, we consider unit shocks to the standardized uncertainty series to ensure that possible differences in the impulse responses between Germany and the United States can be traced back to differences in the transmission mechanism and not to differences in the shock size.

Figure 3.2 plots the impulse responses from the four separate VARs for Germany and for the United States after an innovation to $FDISP^{GER}$ and $FDISP^{US}$, respectively. The impulse response of the spread-variable is calculated as the difference between the response of the external finance cost and the riskless rate. The responses in the first two rows are estimated with corporate bond yields. The results for Germany are depicted in the first row, the second row covers the responses for the United States. In Germany the spread increases by 20 basis points on impact and reaches a maximum of 40 basis points five months after the initial shock. Afterward, the spread decreases very slowly. The response of the spread in the United States is very similar. After an increase of 25 basis points on impact, the spread reaches a maximum of 45 basis points after six months; the following decrease is gradual. Looking at the two components of the spread separately, one sees that corporate bond yields and government bond yields move in *opposite* directions. In both countries the government bond yield decreases – the two series reach their minimum after about one and a half years. In contrast, the corporate bond yield increases in the two countries. In Germany the yield reaches a maximum of about 20 basis points after three months; in the United States it is 35 basis points after six months. The corporate bond yield in the United States reverts back more slowly than it does in Germany.

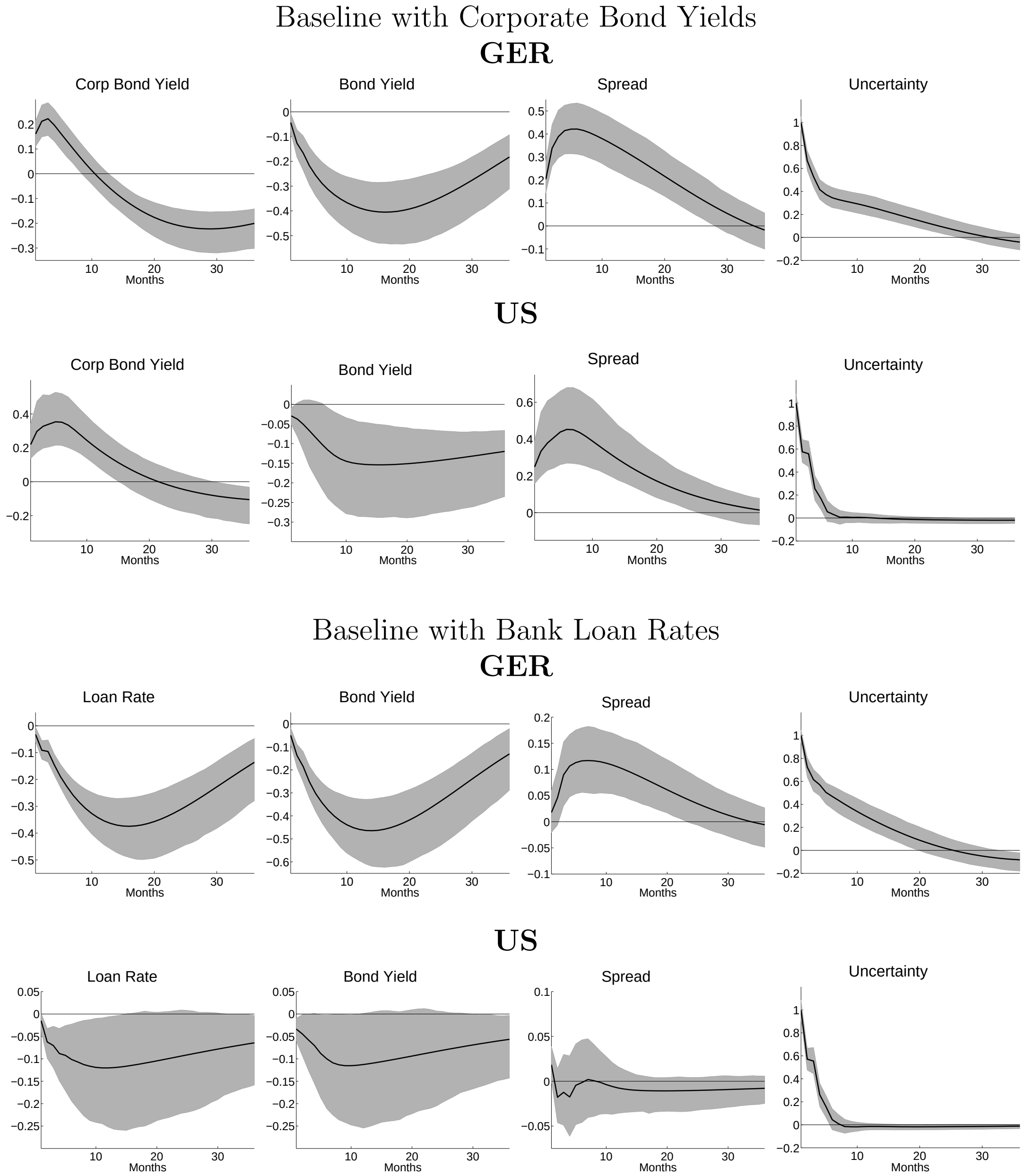
The last two rows in Figure 3.2 plot responses from models with bank loan rates instead of corporate bond yields. The results for Germany are shown in the first row, the second row depicts the responses for the United States. In Germany the credit spread increases but not as much as the spread calculated from corporate bond yields. The maximum increase is 10 basis points and is reached after seven months. The return to steady state is gradual. In the United States the increase in the spread is even smaller than in Germany; the spread increases insignificantly by two basis points on impact; afterward the response remains insignificant. Decomposing the spread into its two parts, it is noted

[53] A similar ordering can be found in Gilchrist, Sim, and Zakrajsek (2014) and Leduc and Liu (2015).

that bank loan rates and government bond yields move in the *same* direction. Loan rates in Germany have decreased by 35 basis points after 15 months. In the United States the loan rate reaches its minimum of roughly 10 basis points after a year. The return to steady state is sluggish in both countries.

As discussed in the introduction, firms in the Euro Area still finance a large share of their projects with bank loans. Therefore, in bank-based financial systems, the bank loan rate comes closer to the true financing costs than corporate bond yields. Therefore, comparing the corporate bond spread for the United States and the bank loan spread for Germany, we find that spreads in market-based financial systems (U.S.) increase more than those in bank-based systems (Germany) after a surprise increase in uncertainty. This can be explained by the fact that loan rates fall while corporate bond yields rise.

Figure 3.2: Impulse Responses to Uncertainty Shock for Germany and the United States



Notes: The responses are obtained from estimating a 3-variables monthly VAR system for Germany and the United States, respectively. The responses in the first two rows are estimated from corporate bond yields, the last two rows are estimated from bank loan rates. The first and third row show responses for Germany; the second and fourth row for the United States. To identify the uncertainty shock, a Cholesky decomposition is used. Uncertainty is ordered first. The shock is a unit shock to the standardized uncertainty series $FDISP^{GER}$ and $FDISP^{US}$, respectively. The sample period is from 2003M1-2013M12. The black solid line is the point estimate, the gray shaded areas are 95% confidence bands.

3.3.2 Robustness

The results from the baseline model reveal that loan rates behave differently than corporate bond yields after innovations in uncertainty. We now conduct a battery of tests to check the robustness of the baseline results.[54]

In the first robustness check we include a real variable (log of production) in the baseline VAR with the purpose of discovering whether changes in production due to the uncertainty shock result in different interest rate dynamics. The activity variable is ordered first, reacting to uncertainty with a lag. Figure 3.3 presents the impulse responses of the interest rates and the spread for Germany and for the United States. The qualitative picture remains the same: the spread increases in both countries, government bond yields fall, corporate bond yields increase, and loan rates drop. The U.S. corporate bond spread increases more than the German bank loan spread.

In the second robustness check we use an alternative measure of economic activity (log of employment instead of log of production). Figure 3.4 shows that the results of this variation are qualitatively very similar to the baseline results. In the case of the United States, we find that the the bank loan spread temporarily declines.

The next test adds a policy rate measure to the four-variable VAR from the first robustness check so as to control for the possibility that monetary policy reacts to uncertainty shocks by decreasing the policy rate in order to stimulate the economy. The policy rate is ordered last, reflecting the idea that uncertainty has an immediate effect on short-term interest rates (Gilchrist, Sim, and Zakrajsek, 2014).[55] For Germany we use the Euro OverNight Index Average (EONIA) as a monetary policy measure; for the United States it is the effective federal funds rate. The impulse responses are plotted in Figure 3.5. Compared to the baseline, the impulse responses are qualitatively the same. Uncertainty shocks are followed by corporate bond yield increases and loan rate decreases. The increase in the bank loan spread in Germany is smaller than the rise in the corporate bond spread in the United States.

In the next robustness check we change the ordering of the variables in the VAR. In all prior tests, uncertainty is ordered before the interest rate variables, implying that surprise changes in uncertainty have a contemporaneous effect.

[54] The responses of the variables that are added to the baseline VARs are as expected, however, they are not presented here to not overdo the number of plots.

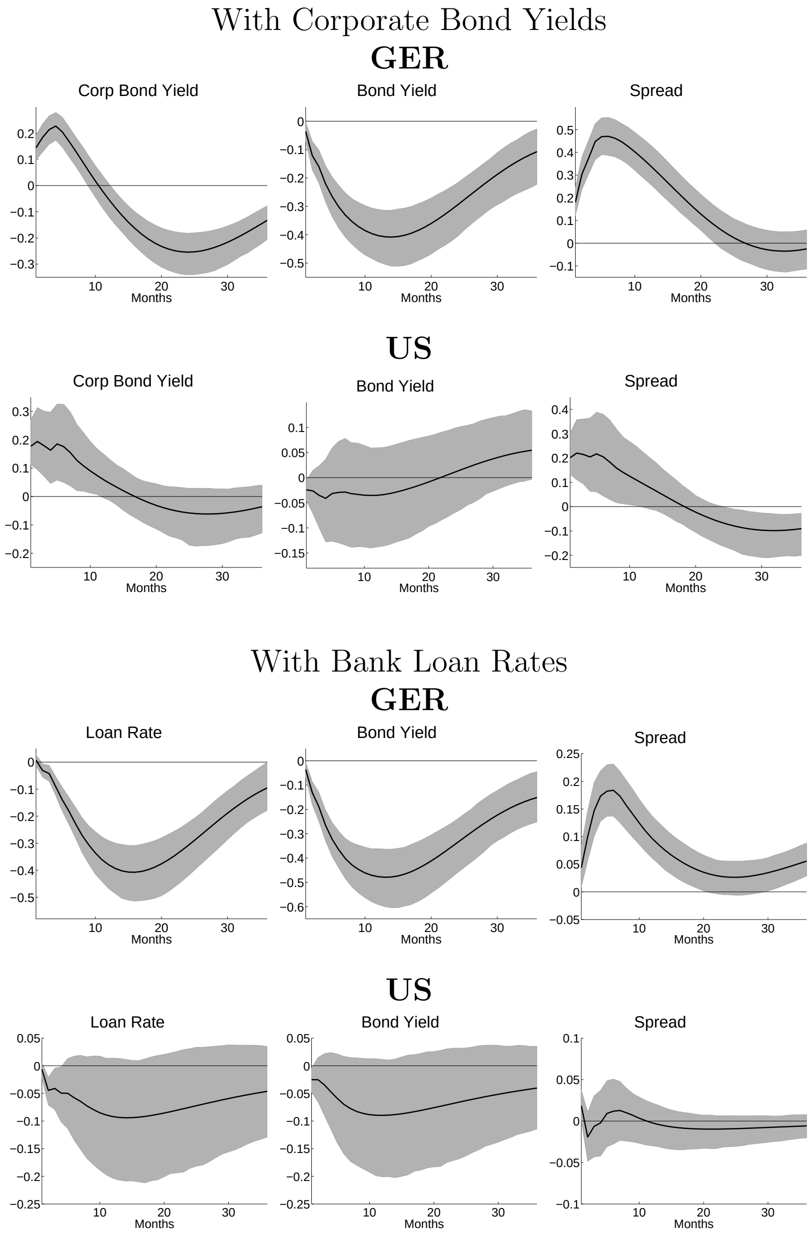
[55] Ordering the policy rate before the corporate bond yield, reflecting the idea that the latter may react on impact to innovations in uncertainty, does not change the results.

Bekaert, Hoerova, and Lo Duca (2013) and Popescu and Smets (2010) argue that when forming beliefs, agents use all current macroeconomic information available and, therefore, uncertainty may react contemporaneously to changes in interest rates. We modify the baseline 3-variables VAR accordingly and order uncertainty last. Impulse responses are shown in Figure 3.6. Ordering uncertainty last does not change the qualitative results. However, the quantitative responses of the models with the corporate bond yield are much smaller. For the United States, the maximum increase in the spread is 15 basis points compared to 45 basis points in the VAR from the baseline. In the case of Germany, the respective number is 30 basis points compared to 40 basis points from the baseline. The maximum increase in the corporate bond yield is cut in half in both countries compared to the baseline. This result goes in the direction of Gilchrist, Sim, and Zakrajsek (2014), who find that U.S. corporate bond spreads do not react significantly to hikes in uncertainty when the credit spread variable is ordered before uncertainty.

In the next exercise we check whether using different bank loan rates has implications for the impulse responses. For Germany we now use the loan rate on outstanding loans (with a maturity of one year) instead of new loans to check whether banks also decrease interest rates on loans that were already granted. For the U.S. we used the bank prime rate so far, which might be problematic. The prime rate is used to price short-term business loans that have a maturity of less than a year; there could be a maturity mismatch with the corresponding riskless rate. Furthermore, the prime rate is usually charged to relatively low-risk firms. Therefore, we replace the prime rate with the (quarterly) loan rate to nonfinancial corporations with a maturity of up to one year. This series is part of the Survey of Terms of Business Lending and is collected quarterly from a random sample of about 300 U.S. banks (Brady, English, and Nelson, 1998). Due to the lower frequency, we linearly interpolate to be able to perform the analysis at a monthly frequency. Figure 3.7 shows that the responses for Germany and the United States remain qualitatively the same as in the baseline. The result for Germany is particularly interesting. Even if the bank has already granted the loan with a corresponding loan rate, an increase in uncertainty leads the bank to reduce the loan rate of the existing loan. This is additional evidence in favor of the relationship story and against the risk-shifting motive that is discussed in Section 3.4.3. Therefore, the bank tries to accommodate the negative effects of the shock on the firm by reducing the lending rate.

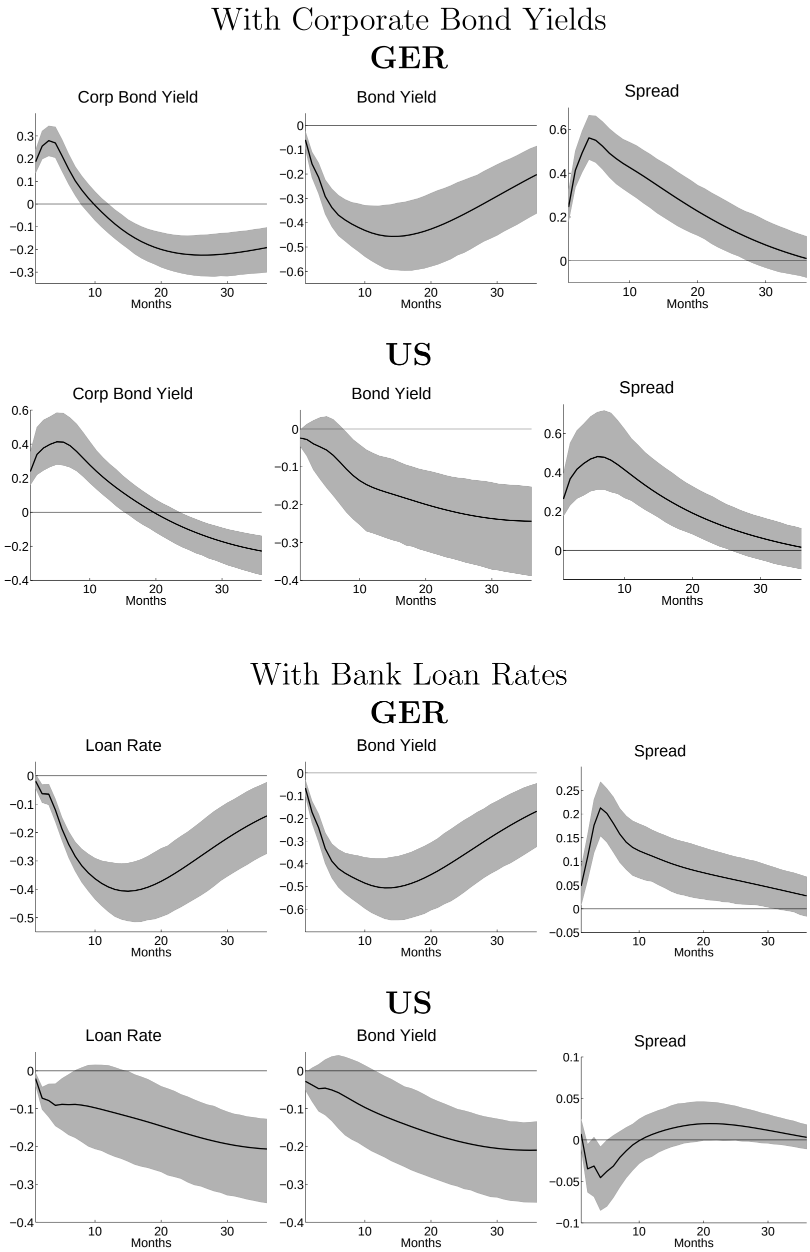
All the VARs used to this point are estimated with three lags. The Breusch-Godfrey test does not reject the null hypothesis of no residual autocorrelation in all these models. However, there remains the concern as to whether the relatively low number of lags truly captures the system's dynamics, especially since it is estimated on a monthly frequency. Estimation with 12 lags is not feasible due to the short sample period. Implementing 12 lags, however, is possible using a Bayesian framework and assuming appropriate priors. We estimate the baseline 3-variables and 5-variables system with 12 lags including additional information in the form of a Minnesota-type prior. For technical details on the Bayesian VAR (BVAR), see Section 3.C in the Appendix. For the uncertainty series we impose the prior belief of white noise; for the other variables that of a random walk. The impulse responses are depicted in Figures 3.8 and 3.9. The results of decreasing loan rates and increasing corporate bond yields continue to hold. However, the responses from the BVARs are less persistent in both countries. In the two countries the median responses of the corporate bond spread are back in equilibrium after one to two years compared to roughly three years in the baseline VARs. A similar result is found for the bank loan spread in Germany. Loan Rates in the United States are significantly below steady state for about half a year compared to one and a half years in the baseline VAR.

Figure 3.3: Robustness I: Impulse Responses to Uncertainty Shock with Four Variables for Germany and the United States



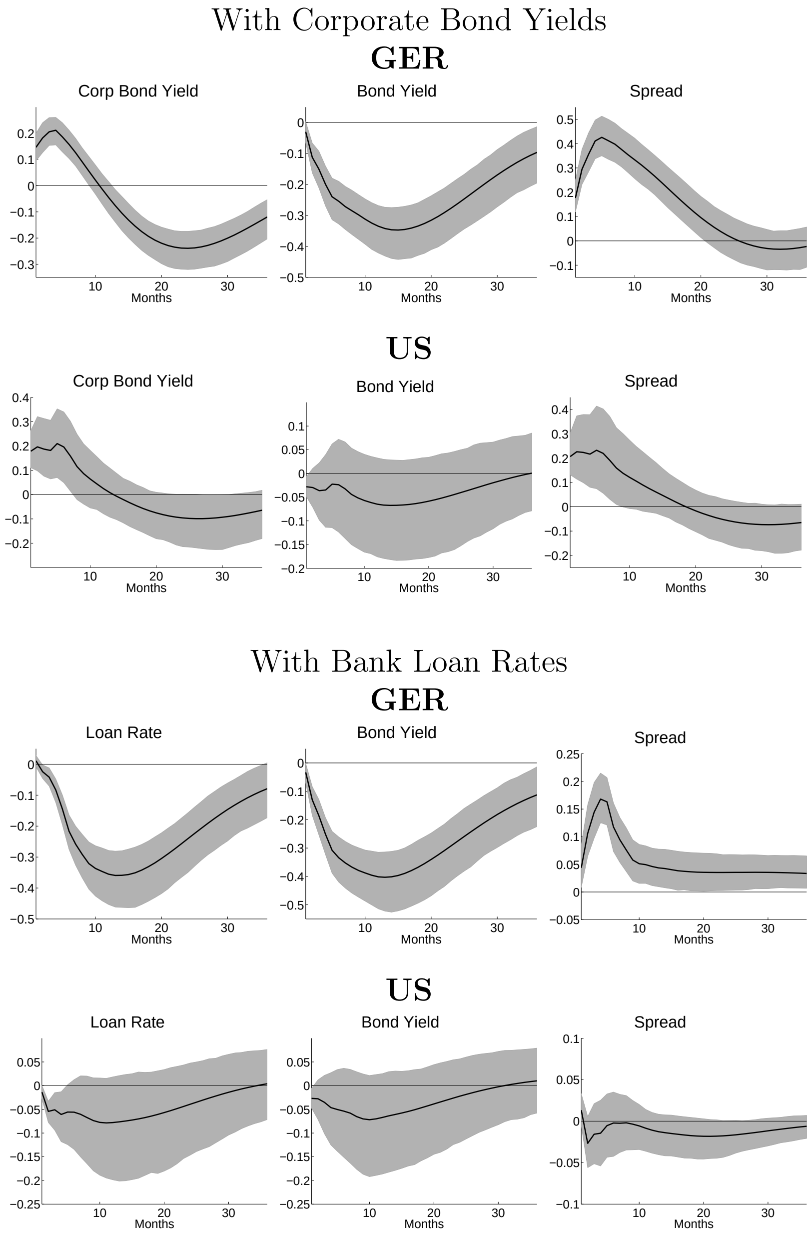
Notes: The responses are obtained from estimating a 4-variables monthly VAR system for Germany and the United States, respectively. The responses in the first two rows are estimated from corporate bond yields, the last two rows are estimated from bank loan rates. The first and third row show responses for Germany; the second and fourth row for the United States. The additional variable (compared to the baseline) is production. To identify the uncertainty shock, a Cholesky decomposition is used. Uncertainty is ordered second after the activity variable. The shock is a unit shock to the standardized uncertainty series $FDISP^{GER}$ and $FDISP^{US}$, respectively. The sample period is from 2003M1-2013M12. The black solid line is the point estimate, the gray shaded areas are 95% confidence bands.

Figure 3.4: Robustness II: Impulse Responses to Uncertainty Shock with Four Variables (Employment Instead of Production) for Germany and the United States



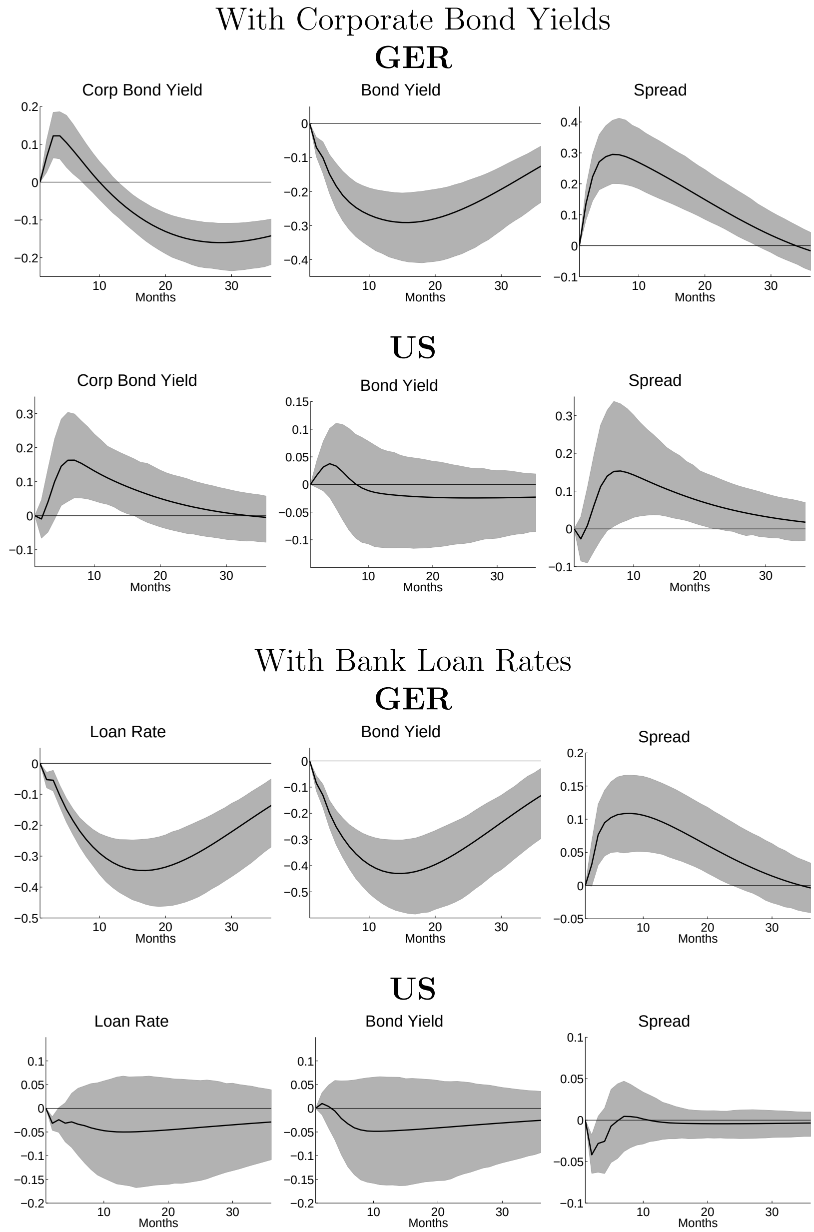
Notes: The responses are obtained from estimating a 4-variables monthly VAR system for Germany and the United States, respectively. The responses in the first two rows are estimated from corporate bond yields, the last two rows are estimated from bank loan rates. The first and third row show responses for Germany; the second and fourth row for the United States. The additional variable (compared to the baseline) is employment. To identify the uncertainty shock, a Cholesky decomposition is used. Uncertainty is ordered second after the activity variable. The shock is a unit shock to the standardized uncertainty series $FDISP^{GER}$ and $FDISP^{US}$, respectively. The sample period is from 2003M1-2013M12. The black solid line is the point estimate, the gray shaded areas are 95% confidence bands.

Figure 3.5: Robustness III: Impulse Responses to Uncertainty Shock with Five Variables for Germany and the United States



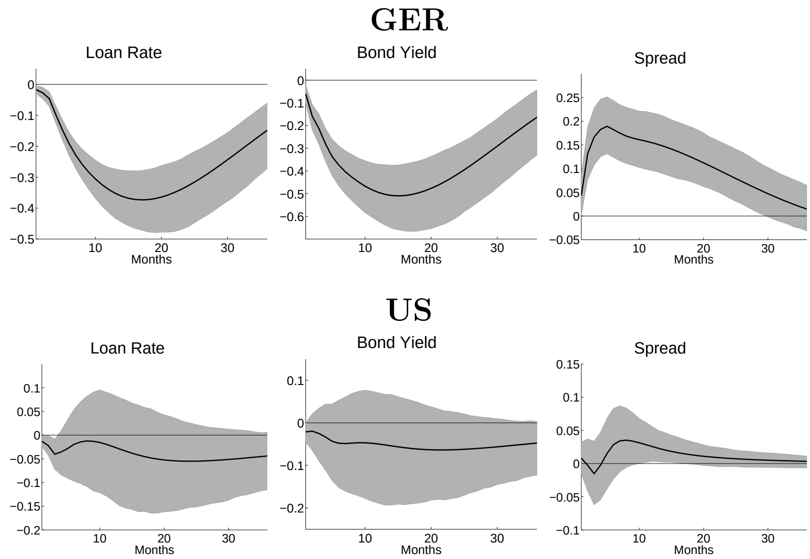
Notes: The responses are obtained from estimating a 5-variables monthly VAR system for Germany and the United States, respectively. The responses in the first two rows are estimated from corporate bond yields, the last two rows are estimated from bank loan rates. The first and third row show responses for Germany; the second and fourth row for the United States. The additional variables (compared to Robustness I) are the EONIA rate for Germany and the Fed Funds rate for the United States. To identify the uncertainty shock, a Cholesky decomposition is used. Uncertainty is ordered after the activity variable; the policy rate is ordered last. The shock is a unit shock to the standardized uncertainty series $FDISP^{GER}$ and $FDISP^{US}$, respectively. The sample period is from 2003M1-2013M12. The black solid line is the point estimate, the gray shaded areas are 95% confidence bands.

Figure 3.6: Robustness IV: Impulse Responses to Uncertainty Shock with Three Variables for Germany and the United States; Uncertainty Ordered After the Interest Rate Variables



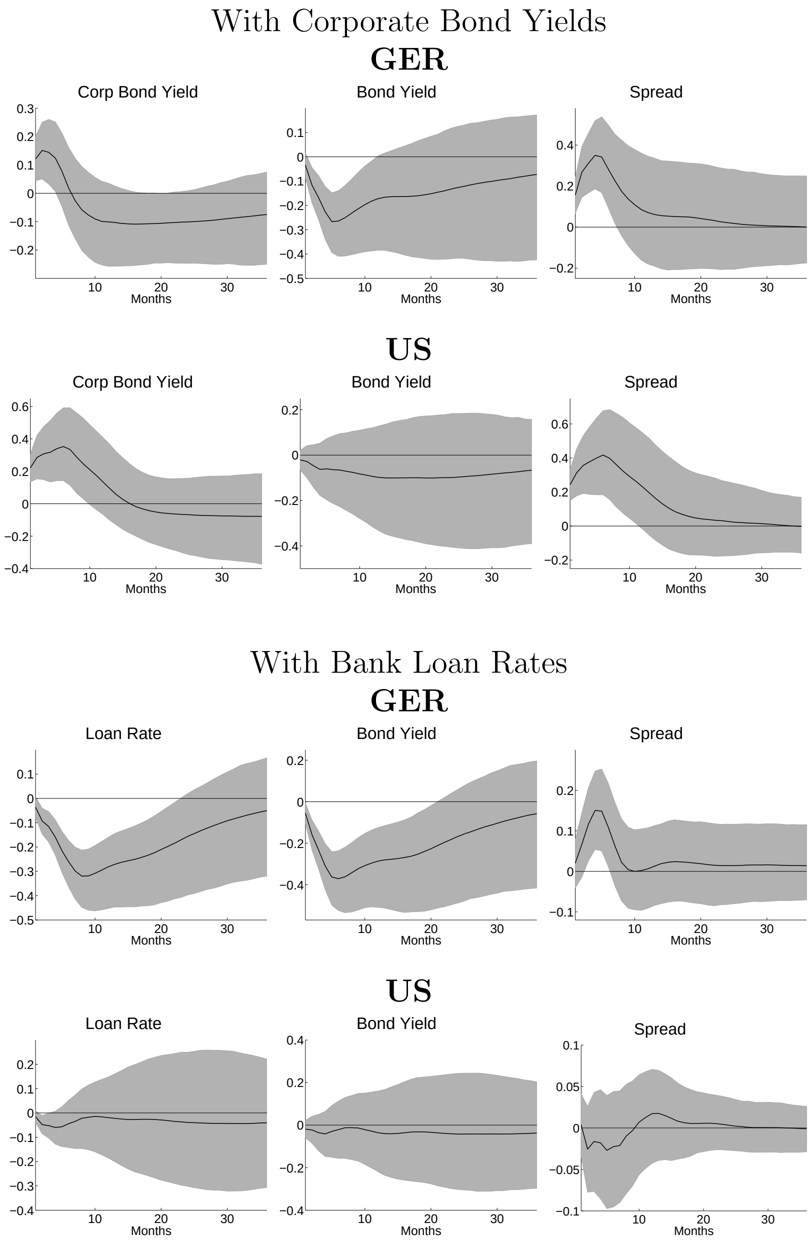
Notes: The responses are obtained from estimating a 3-variables monthly VAR system for Germany and the United States, respectively. The responses in the first two rows are estimated from corporate bond yields, the last two rows are estimated from bank loan rates. The first and third row show responses for Germany; the second and fourth row for the United States. To identify the uncertainty shock, a Cholesky decomposition is used. Uncertainty is ordered last. The shock is a unit shock to the standardized uncertainty series $FDISP^{GER}$ and $FDISP^{US}$, respectively. The sample period is from 2003M1-2013M12. The black solid line is the point estimate, the gray shaded areas are 95% confidence bands.

Figure 3.7: Robustness V: Impulse Responses to Uncertainty Shock with Three Variables for Germany and the United States (Different Bank Loan Rates)



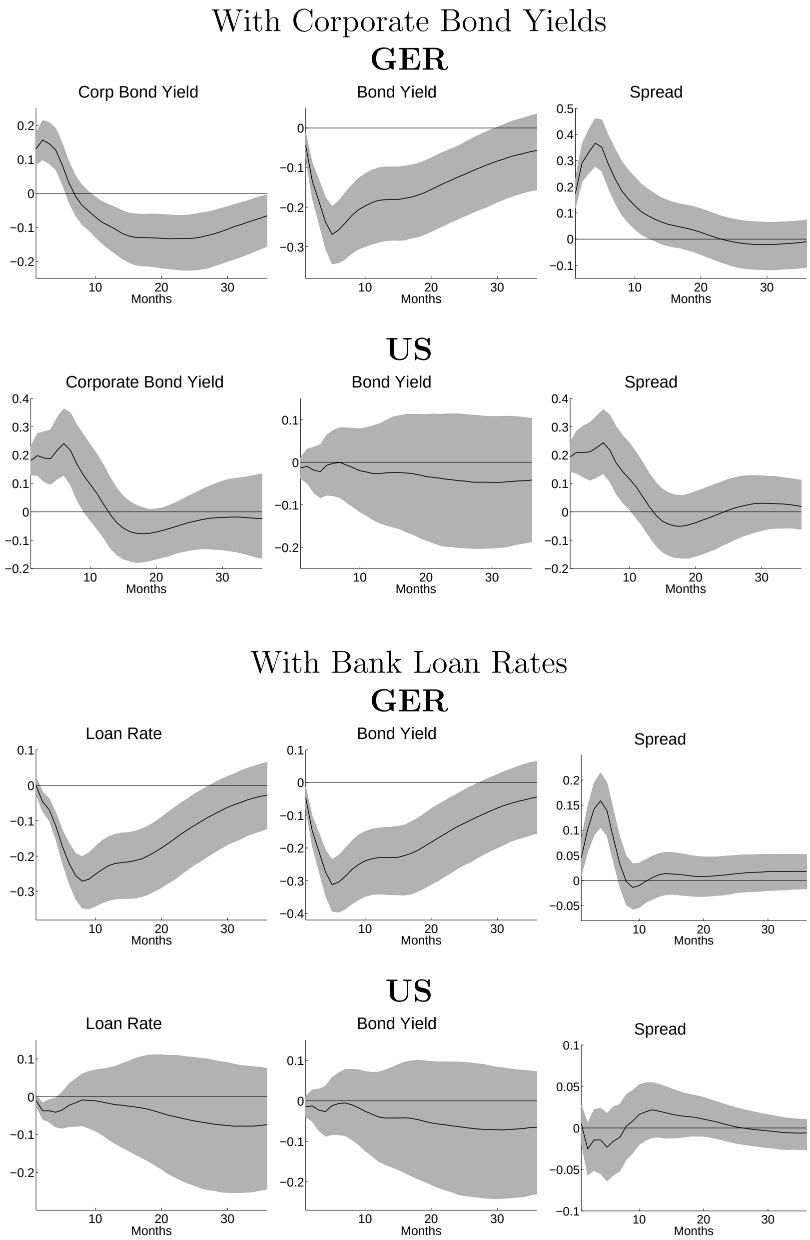
Notes: The responses are obtained from estimating a 3-variables monthly VAR system for Germany and the United States, respectively. For Germany, we use the loan rate on outstanding loans with a maturity of one year. For the United States, we use the loan rate to nonfinancial corporations with a maturity of up to one year; to transform the series from a quarterly to a monthly frequency, the series is interpolated. To identify the uncertainty shock, a Cholesky decomposition is used. Uncertainty is ordered first. The shock is a unit shock to the standardized uncertainty series $FDISP^{US}$. The sample period is from 2003M1-2013M12. The black solid line is the point estimate, the gray shaded areas are 95% confidence bands.

Figure 3.8: Robustness VI: Impulse Responses to Uncertainty Shock with Three Variables for Germany and the United States from a Bayesian VAR with 12 Lags



Notes: The responses are obtained from estimating a 3-variables monthly Bayesian VAR system with 12 lags and a constant. The responses in the first two rows are estimated from corporate bond yields, the last two rows are estimated from bank loan rates. The first and third row show responses for Germany; the second and fourth row for the United States. To identify the uncertainty shock, a Cholesky decomposition is used. Uncertainty is ordered first. The shock is a unit shock to the standardized uncertainty series $FDISP^{GER}$ and $FDISP^{US}$, respectively. The sample period is from 2003M1-2013M12. The black solid line is the point estimate, the gray shaded areas are 68% error bands.

Figure 3.9: Robustness VII: Impulse Responses to Uncertainty Shock with Five Variables for Germany and the United States from a Bayesian VAR with 12 Lags



Notes: The responses are obtained from estimating a 5-variables monthly Bayesian VAR system with 12 lags and a constant. The responses in the first two rows are estimated from corporate bond yields, the last two rows are estimated from bank loan rates. The first and third row show responses for Germany; the second and fourth row for the United States. To identify the uncertainty shock, a Cholesky decomposition is used. Uncertainty is ordered second. The shock is a unit shock to the standardized uncertainty series $FDISP^{GER}$ and $FDISP^{US}$, respectively. The sample period is from 2003M1-2013M12. The black solid line is the point estimate, the gray shaded areas are 68% error bands.

3.4 Theoretical Model

The empirical part of this paper reveals that uncertainty events are accompanied by increases in the corporate bond yield and decreases in the bank loan rate. The current section has two parts. In the first part, we check whether a DSGE model of the type used in the literature on uncertainty and financial frictions implies increasing or decreasing lending rates after an innovation in uncertainty. The model predicts increasing rates; therefore, in the second part, we use a partial equilibrium model and show that the introduction of relationship lending can explain the different responses of banks and the capital market to uncertainty shocks.

3.4.1 DSGE Model with Financial Frictions and Uncertainty Shocks

The model we rely on is basically the model used in much of the literature on uncertainty and financial frictions (see Cesa-Bianchi and Fernandez-Corugedo, 2014, Christiano, Motto, and Rostagno, 2010, 2014, Chugh, 2014, Dorofeenko, Lee, and Salyer, 2008, Fendoglu, 2014, Fernández-Villaverde, 2010, Hafstead and Smith, 2012) and thus we describe it only briefly here. The model is based on Bernanke, Gertler, and Gilchrist (1999) with the addition of an idiosyncratic uncertainty process as in Fernández-Villaverde (2010). It includes a representative household, a representative final good producer, a continuum of monopolistically competitive intermediate good producers, a representative capital good producer, a continuum of entrepreneurs, a financial intermediary (henceforth called a bank), and a central bank. Financial frictions are introduced through an asymmetric information problem between borrowers (entrepreneurs) and lenders (the bank) in the form of CSV. We implement idiosyncratic uncertainty by assuming that each entrepreneur draws an idiosyncratic productivity shock from a distribution with time-varying volatility. For more details on the model, see Appendix 3.D.

Calibration

The model is simulated based on two calibration strategies. The first exercise is specifically set up for the case of Germany. In the second variant, we check whether the results also hold using a sensible range for each of the parameters.

Calibration I The time unit is a quarter. Table 3.1 summarizes the parameter values for the first calibration exercise. The discount factor β is set to 0.995, which is in line with the observed 2.0% annual yield on German government bond yields with a maturity of one year. For the next few parameters we use conventional estimates reported in the literature. The parameter for relative risk aversion ϑ is set to 1.0 and the inverse of the Frisch elasticity of labor supply ϕ to 1.0. We set χ, the relative weight of labor in the utility function, to 6.727 so that the household spends one-third of the time working in steady state. The capital share in production α is set to 0.36. The elasticity of substitution across goods ϵ is set to 6.0, implying a 20% price markup. Bachmann, Born, Elstner, and Grimme (2013) estimate that on average 32% of German manufacturing firms change their price each quarter, implying a Calvo price stickiness parameter θ of 0.68.

Table 3.1: Calibrated Parameters

Parameter	Value	Description
β	0.995	Discount factor
ϑ	1.0	Relative risk aversion
ϕ	1.0	Inverse of the Frisch elasticity of labor supply
α	0.36	Capital share in production
ϵ	6	Elasticity of substitution between goods
θ	0.68	Calvo price stickiness
δ	0.023	Depreciation rate
ϕ_k	10	Investment adjustment cost
γ_r	0.95	Interest rate smoothing in Taylor rule
γ_π	1.5	Weight on inflation in Taylor rule
γ_y	0.5	Weight on output in Taylor rule
μ	0.23	Monitoring costs
γ_e	0.978	Survival probability of entrepreneurs
$\bar{\omega}$	0.3721	Steady state default threshold value
σ_ω	0.3985	Steady state standard deviation of uncertainty
ρ_σ	0.82	Persistence in uncertainty shock
η_σ	0.013	Volatility of uncertainty shock

The depreciation rate δ is computed from German national accounting data (VGR) for nonfinancial firms. Following Bachmann and Bayer (2013), who estimate a value of 9.4% on a yearly frequency, we use a value of 0.023 for δ. We set the adjustment cost for capital ϕ_k to 10, implying an elasticity of the price of capital with respect to the investment-to-capital ratio of 0.25 in steady state. Bernanke, Gertler, and Gilchrist (1999) state that the elasticity should lie between 0 and 0.5.

The coefficients in the Taylor rule are the following: for the interest rate smoothing parameter γ_r we use a value of 0.95, for the weight on inflation $\gamma_\pi = 1.5$, and for the weight on output $\gamma_y = 0.5$.

The remaining parameters (the monitoring cost μ, the fraction of entrepreneurs' profit that is consumed $(1 - \gamma_e)$, the default threshold $\bar{\omega}$, and the standard deviation of idiosyncratic productivity σ_ω) are related to the credit friction and are set so as to achieve reasonable steady state values for the entrepreneurial default rate, the leverage ratio, and the spread between the loan rate and the riskless rate. The steady state default probability equals 4.5% per year. Estimates for the Euro Area range between 3% (see von Heideken, 2009) and 4.96% (see De Fiore and Uhlig, 2011). The steady state leverage ratio K/N equals 1.6, which is the average value found for German nonfinancial corporations in the Euro Area Accounts for the time period 2003 to 2013. The steady state spread is 145 basis points in annual terms, which is the historical average between the spread of the loan rate of new loans to non-financial firms of one-year maturity and the government bond yield of the same maturity. The steady state values of selected variables and ratios are shown in Table 3.2.

To derive values for the idiosyncratic uncertainty process for Germany, we fit an AR(1) process to the uncertainty series $FDISP^{GER}$ used in the empirical part. $FDISP^{GER}$ is transformed to a quarterly frequency by taking three-month averages. The persistence of uncertainty ρ_{σ_ω} is estimated to be 0.82; the volatility of the uncertainty shock η_σ is 0.013. Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2012) estimate values of 0.76 and 0.049, respectively, for the United States from the Census panel of manufacturing establishments. Using firm-level data for 7,000 large U.S. manufacturing plants, Chugh (2014) estimates a persistence parameter and a standard deviation of 0.83 and 0.0033, respectively. Bachmann and Bayer (2013) estimate values of 0.58 and 0.0037, respectively, using firm-level data for almost the entire German nonfinancial private business sector; however, the data are of an annual frequency.[56] Finally, Christiano, Motto, and Rostagno (2010) estimate 0.91 and 0.041, respectively, for the Euro Area through Bayesian estimation using macro-financial data. Therefore, our estimate of the persistence parameter is most similar to that of Chugh (2014); our volatility estimate is larger than the

[56] Fitting an AR(1) process to the uncertainty series $FDISP^{GER}$, averaged to an annual frequency, gives 0.46 and 0.018 for the persistence parameter and the standard deviation, respectively. Chugh (2014) estimates 0.48 and 0.0276, respectively, at an annual frequency.

Table 3.2: Selected Steady State Values and Ratios (from First Calibration Exercise)

Variables	Value	Description
χ	6.727	Relative weight of labor in utility
C/Y	0.71	Household consumption relative to output
C^e/Y	0.10	Entrepreneurial consumption relative to output
K/Y	7.19	Capital relative to output
I/Y	0.18	Investment relative to output
$\mu G(\bar{\omega})R^K K/Y$	0.0061	Monitoring costs relative to output
Targeted Variables in Steady State		
$F(\bar{\omega})$	4,5% p.a.	Default probability
K/N	1.6	Leverage
spread	145 bpts (ann.)	Ratio of loan rate R^B to riskless rate R
R	2.0	Riskless rate (annualized)
H	0.33	Steady state labor

values obtained by Bachmann and Bayer (2013) and Chugh (2014) but smaller than those of Christiano, Motto, and Rostagno (2010) and Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2012).

Calibration II To show that the results in the next section are not dependent on calibrating the model specifically for Germany, we undertake a second calibration exercise in which we define a sensible interval for each parameter. Table 3.3 summarizes the parameter values.

The discount factor β is allowed to vary in the interval [0.985, 0.997], which implies an annual steady state riskless rate between 1.2-6.2%. The range for the parameter for relative risk aversion ϑ is set between [1, 4], that of the inverse of the Frisch elasticity of labor supply ϕ between [0, 4], and that of the capital share in production α between [0.2, 0.5]. The elasticity of substitution across goods ϵ is allowed to vary in the interval [5, 100], while the Calvo price stickiness parameter θ is set between [0.6, 0.9]. The interval for ϵ implies that the price markup will be between 1-25%; the range for θ means that the average quarterly likelihood of a price changes is between 10-40%.

We allow for variation in the depreciation rate $\delta \in [0.01, 0.05]$ and the adjustment cost for capital $\phi_k \in [0.01, 12]$. Together, these two parameter ranges imply that the elasticity of the price of capital with respect to the investment-to-capital ratio will be between 0.0001 and 0.6.

Table 3.3: Parameter Ranges (Second Calibration Exercise)

Parameter	Value	Description
β	[0.985, 0.997]	Discount factor
ϑ	[1, 4]	Relative risk aversion
ϕ	[0, 4]	Inverse of the Frisch elasticity of labor supply
α	[0.2, 0.5]	Capital share in production
ϵ	[5, 100]	Elasticity of substitution between goods
θ	[0.6, 0.9]	Calvo price stickiness
δ	[0.01, 0.05]	Depreciation rate
ϕ_k	[0.01, 12]	Investment adjustment cost
γ_r	[0.9, 0.99]	Interest rate smoothing in Taylor rule
γ_π	[1, 3]	Weight on inflation in Taylor rule
γ_y	[0, 0.99]	Weight on output in Taylor rule
ρ_σ	[0.7, 0.9]	Persistence in uncertainty shock
η_σ	[0.0033, 0.07]	Volatility of uncertainty shock
$F(\bar{\omega})$	[0.03, 0.045]	Default probability
K/N	[1.2, 1.95]	Leverage
$spread$	[120, 300]	Ratio of loan rate R^B to riskless rate R

For the coefficients in the Taylor rule we set the following value ranges: the interest rate smoothing parameter γ_r is allowed to vary between [0.9, 0.99], the central bank's response to deviations of inflation from steady state γ_π is between [1, 3], and the weight on output fluctuations γ_y varies between [0, 0.99].

The parameters related to financial friction in the model (the monitoring cost μ, the exogenous fraction of entrepreneurial consumption $(1 - \gamma_e)$, the default threshold $\bar{\omega}$, and the standard deviation of idiosyncratic productivity σ_ω) are set so that the target variables are in the following intervals. The steady state default probability varies between [3.0%, 4.5%] in annual terms. The steady state leverage ratio K/N is set between [1.2, 1.95], which is the maximum range reported by Christiano, Motto, and Rostagno (2010) for the Euro Area and the United States. In line with the literature on the financial accelerator, the steady state spread is allowed to vary between [120, 300] basis points.

Finally, the persistence of the uncertainty shock ρ_{σ_ω} is restricted to the interval [0.7, 0.9], while the volatility of the uncertainty shock η_σ is set between [0.0033, 0.07].

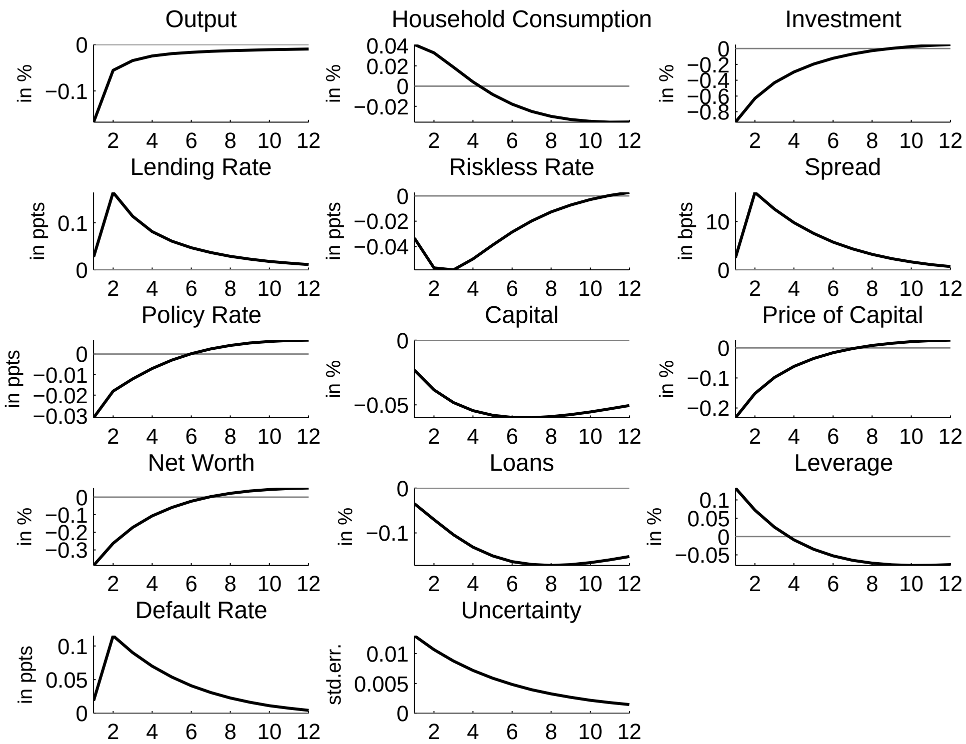
Results

Figure 3.10 shows the impulse responses after a surprise increase in idiosyncratic uncertainty for the first calibration variation. A higher dispersion of the idiosyncratic shock distribution implies that some entrepreneurs will draw larger idiosyncratic shocks and others smaller ones. This leads to a higher probability of default. Lenders demand a risk premium as insurance against the borrowers' higher default risk. As credit spreads increase, external financing becomes more expensive for entrepreneurs and, therefore, they reduce their demand for capital. Investment drops and so does output. Capital prices decrease, which has a depressing effect on entrepreneurs' net worth. Subsequently, leverage increases and entrepreneurs need to deleverage. The reduction in aggregate demand pushes down marginal costs and prices. Monetary policy attempts to counteract these dynamics by cutting the policy rate.

In the model, the drop in the policy rate goes hand in hand with an increase in the lending rate. In the previous section of the paper, we observe empirically that the policy rate decreases and corporate bond yields increase after an innovation in uncertainty. Therefore, the DSGE model is able to replicate the empirical findings for capital market behavior after an uncertainty shock. Capital market participants are confronted with a higher default risk on the part of the entrepreneurs from whom they buy corporate bonds and demand a risk premium, leading to an increase in bond yields.

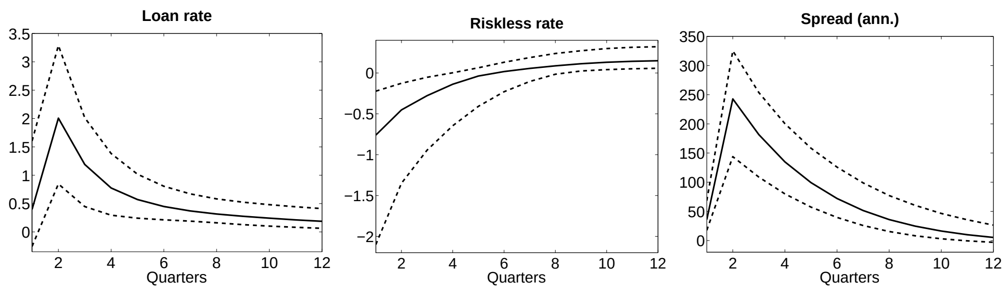
In the remainder of this section we check whether the model's finding of increasing lending rates is robust with respect to calibration. This is where the second calibration exercise, in which we define intervals for each parameter and assume that values are uniformly distributed over the respective parameter range, comes into play. We draw a value for each parameter and calculate impulse responses. This procedure is repeated 10,000 times. Figure 3.11 presents the median and the 16th and 84th percentiles. The impulse response of the lending rate is still positive across all combinations of parameter values. Therefore, the stylized fact that corporate bond yields increase after an uncertainty shock is a robust feature of the DSGE model with CSV.

Figure 3.10: Uncertainty Shock in DSGE Model



Notes: Impulse responses to a one standard deviation increase in uncertainty using the calibration for Germany (Calibration I).

Figure 3.11: Uncertainty Shock in DSGE Model: Sensitivity



Notes: Impulse responses to a one standard deviation increase in uncertainty (Calibration II). Median, 16th and 84th percentiles of simulation with 10,000 draws. In each draw each parameter is drawn from a sensible range of values. The first two plots are expressed in percentage points; the third plot in basis points.

3.4.2 Partial Equilibrium Model with Relationship Lending

The previous section demonstrates that a DSGE model with CSV and uncertainty can replicate the behavior of the capital market: a surprise increase in uncertainty leads capital market participants to demand a higher risk premium as compensation for the higher default risk, leading to an increase in the lending rate. This section presents a simple partial equilibrium model with CSV and the possibility for banks to form long-term relationships with borrowers. On the one hand, this model replicates the finding that capital markets charge higher lending rates in periods of high uncertainty. On the other hand, the model shows that the bank's ability to establish a relationship with borrowers implies comparatively lower bank loan rates in response to an uncertainty shock.

When capital markets and banks act as lenders they face asymmetric information problems vis-à-vis their borrowers. In contrast to the capital market, banks are able to establish long-term relationships with their borrowers, which have the effect of reducing these asymmetries over time. Reducing the information asymmetry problem in terms of the CSV model means that the bank's costs of monitoring the borrower are lowered, which make a relationship-firm's default less costly for the bank. Lower bankruptcy costs enable the bank to charge higher lending rates compared to the capital market.[57] If this markup is high enough, that is, if the reduction in bankruptcy costs is sufficiently large, it is optimal for the bank to temporarily offer loan rates in times of high uncertainty that are relatively lower than rates on the capital market, because the uncertainty event is interpreted by the bank as a short-lived setback in the firm's prospects. Holding interest rates low, the bank hopes to keep the borrower out of default, collect more information about the firm during the uncertainty period and subsequently charge relatively higher rates in tranquil times and reap profits.[58]

[57] De Fiore and Uhlig (2011) present a model explaining the differences in corporate financing between the United States and the Euro Area. They find that the best model fit is found for lower levels of monitoring costs in the Euro Area compared to the United States. The Euro Area and, in particular, Germany are characterized by large bank loan financing; therefore, it is reasonable to assume that banks that have formed relationships face lower monitoring costs.

[58] The firm's motivation for having a relationship with the bank is not explicitly modeled. Our model implicitly assumes that switching costs are high enough that it is too expensive for the firm to search for a different bank that offers more favorable lending terms. Another reason could be that the firm hopes to obtain more favorable borrowing terms by revealing proprietary information to the bank (see Greenbaum, Kanatas, and Venezia, 1989).

The basic setup of the model follows Williamson (1987) and Walsh (2003), to which we add the notion of relationship lending. We assume there are two types of agents, a continuum of borrowers (firms) and a lender (a relationship bank or the capital market). The lender is risk neutral. Firms invest in a project with a stochastic payoff $x \in [\underline{x}, \bar{x}]$, which is uniformly distributed. Firms do not have enough own resources for the investments they wish to undertake and thus need resources from a lender. Following Townsend (1979), we assume an asymmetric information problem between borrowers and the lender. The distribution from which the payoffs are drawn is known to both agents. The actual draw, however, is the firm's private information; the lender can observe the (payoff) shock x only by paying a monitoring cost c. This lump-sum cost is introduced to capture the idea that borrowers have more information about their own projects than does the lender.

The firm is able to pay back its debt whenever its revenue, x, is larger than its debt, $R \times B$, where R is the cost of the credit and B is the volume of credit, which is normalized to 1 in the following: we assume that a firm needs one unit of resources to undertake the project.[59] For all $x \geq \hat{x}$, the firm is able to pay back the loan, where the threshold level $\hat{x}$ is the level at which the firm earns just enough from the project to pay back its debt R. Therefore, $\hat{x} = R$ has to hold. After paying back its debt, the firm keeps the residual $(x - R)$. The firm defaults if $x < \hat{x}$; the lender monitors the firm and seizes the share $x - c$. Defaulting firms receive nothing. The firm only borrows from the bank if its expected return is not smaller than zero:

$$\int_{R}^{\bar{x}} (x - R) \frac{1}{\bar{x} - \underline{x}} dx \geq 0 \ . \tag{3.1}$$

The structural difference between banks and the capital market is that banks are able to form long-term relationships with their borrowers, which reduces the monitoring costs. In the following, we assume that relationship banks incur monitoring costs $\tilde{c}$ in regard to firms with which they have formed a relationship. Lending to a firm with no relationship leads to monitoring costs c where $c > \tilde{c}$ holds. c is also the value the capital market cannot retrieve from the borrower's insolvency mass in case of borrower default.

[59] Allowing for a time-varying loan volume would dampen the reaction of the loan rate following an uncertainty shock. Comparatively low lending rates increase the demand for loans, which increases the probability of firm default. This raises the loan rate relatively. Therefore, producing relatively low bank loan rates after uncertainty shocks depends on the interest rate elasticity of loan demand.

In the following, we describe two model economies – one in which firms rely on external financing through capital markets, one in which firms borrow from banks. We analyze what happens with the lending rate on the capital market and the bank loan rate when the two economies are hit by an uncertainty shock, respectively. We assume there are two periods: at the beginning of each period lenders offer contracts to firms who invest in a risky project. At the start of the first period, there is an exogenous increase in uncertainty σ, which effects the return payoff $x_1 \in [\underline{x} - \sigma, \bar{x} + \sigma]$ – that is, the payoff is drawn from a wider distribution. At the beginning of the second period, the uncertainty shock σ has completely abated, such that the project yields a payoff $x_2 \in [\underline{x}, \bar{x}]$, again. Furthermore, we assume that firms which default in the first period are replaced by new firms prior to the second period.[60]

Capital Market By assumption, the capital market cannot establish a long-term relationship with a borrower. Therefore, the capital market solves a simple static optimization problem. The expected return to the lender in the first period is

$$\int_{\underline{x}-\sigma}^{R_1^C} (x - c) \frac{1}{(\bar{x} + \sigma) - (\underline{x} - \sigma)} dx + \int_{R_1^C}^{\bar{x}+\sigma} R_1^C \frac{1}{(\bar{x} + \sigma) - (\underline{x} - \sigma)} dx \qquad (3.2)$$

where R_1^C denotes the rate charged by the capital market (the bond yield) in the first period. The first term of Equation (3.2) is the expected return to the lender if the borrower defaults, which occurs whenever $x < R_1^C$. In this situation, the lender receives the total payoff of the project x net bankruptcy costs c. The second term is the expected return to the lender if the borrower does not default, which holds whenever $x \geq R_1^C$. In this case, the lender receives the payment R_1^C from the borrower. Maximizing Equation (3.2) with respect to the lending rate R_1^C subject to the borrowers' participation constraint (Equation (3.1)) leads to[61]

$$R_1^C = \bar{x} - c + \sigma \ . \qquad (3.3)$$

[60] Due to the simple structure of the model, there is no steady state. Therefore, in response to an uncertainty shock, we can only compare the different reactions of the lending rates on the capital market and the bank market with each other.

[61] The complementary slackness condition implies that the borrower's participation constrain (Equation (3.1)) is only binding for $c = 0$. Since we work with a model of asymmetric information, $c > 0$, and we can drop the Lagrange parameter in the following analysis. This holds for both periods.

An increase in uncertainty σ increases the lending rate R_1^C. Therefore, capital market participants demand to be fully compensated for the rise in default risk. This results is in line with the prediction of the full-fledged DSGE model discussed in the previous section.

In period 2 the component σ of the payoff of the project exogenously vanishes ($\sigma = 0$). The rate charged by the capital market in period 2, R_2^C , equals[62]

$$R_2^C = \bar{x} - c \; . \tag{3.4}$$

Bank In contrast to the capital market, the bank is able to try to form a relationship with its borrowers in the first period in order to reduce the asymmetric information problem in the second period.[63] The bank solves an inter-period maximization problem, in which its decision in the first period effects the outcome in the second period. The expected discounted return to the bank in period 1 is:

$$\begin{aligned}
&\int_{\underline{x}-\sigma}^{R_1^B} (x-c)\frac{1}{(\bar{x}+\sigma)-(\underline{x}-\sigma)}dx + \int_{R_1^B}^{\bar{x}+\sigma} R_1^B \frac{1}{(\bar{x}+\sigma)-(\underline{x}-\sigma)}dx \\
&+\beta\left\{1-\int_{\underline{x}-\sigma}^{R_1^B}\frac{1}{(\bar{x}+\sigma)-(\underline{x}-\sigma)}dx\right\}\left\{\int_{\underline{x}}^{R_2^B}(x-\tilde{c})\frac{1}{\bar{x}-\underline{x}}dx+\int_{R_2^B}^{\bar{x}} R_2^B\frac{1}{\bar{x}-\underline{x}}dx\right\} \\
&+\beta\left\{\int_{\underline{x}-\sigma}^{R_1^B}\frac{1}{(\bar{x}+\sigma)-(\underline{x}-\sigma)}dx\right\}\left\{\int_{\underline{x}}^{\widehat{R}_2^B}(x-c)\frac{1}{\bar{x}-\underline{x}}dx+\int_{\widehat{R}_2^B}^{\bar{x}} \widehat{R}_2^B\frac{1}{\bar{x}-\underline{x}}dx\right\}
\end{aligned} \tag{3.5}$$

where R_1^B denotes the loan rate charged by the bank in period 1 and β is the discount factor. The first term in line 1 is the expected return to the bank if the borrower defaults, the second term is the expected return to the lender if the borrower does not default; in the latter case, the bank receives the payment R_1^B.

[62] The expected return in period 2 is $\int_{\underline{x}}^{R_2^C}(x-c)\frac{1}{\bar{x}-\underline{x}}dx + \int_{R_2^C}^{\bar{x}} R_2^C \frac{1}{\bar{x}-\underline{x}}dx$.

[63] We consider a bank which faces the choice of establishing a new relationship when uncertainty is high. Alternatively, one could think of relationship lending as an "equilibrium phenomenon", i.e. the uncertainty shock hits a steady state of the model in which the bank has already established relationships with borrowers. The bank enjoys an informational advantage compared to the capital market, therefore the steady state bank loan rate is relatively higher than the capital market rate. An increase in uncertainty results in a reduction in the loan rate if the bank values the long-run benefits of continuing the relationship higher than the short-run benefits of increasing the loan rate at the expense of a higher probability of firm default. Therefore, introducing steady state relationship lending would complicate the analysis, while keeping the qualitative results unchanged.

In contrast to the capital market's maximization problem, the bank takes into account the effect its choice of R_1^B will have on the expected discounted return in period 2, which is represented by lines 2 and 3 in Equation (3.5).

Line 2 describes the expected discounted return if a borrower does not default at the end of the first period, which depends on the magnitude of the loan rate R_1^B in the first period. This is represented by the term in the first parenthesis: a low value of R_1^B reduces the probability of borrower default and, therefore, increases the probability that a relationship can be formed between the bank and the firm. Given a firm does not default in period 1, the relationship is formed and the bank collects information about the firm, which reduces the monitoring costs from c to $\tilde{c}$. In case of borrower default in the second period, the bank seizes a higher share of the firm's return, $x - \tilde{c} > x - c$. Otherwise, the bank charges the loan rate R_2^B in period 2.

Line 3 of Equation (3.5) describes the expected discounted return if a borrower defaults at the end of period 1 and no relationship is formed. The probability of this event is denoted by the term in the first parenthesis. In this case, the bank lends to another firm at loan rate $\widehat{R}_2^B$. The bank has not more information about the new firm than the capital market; thus, the bank faces the full asymmetric information problem and monitoring costs are c.

The problem the bank needs to solve is picking the loan rate R_1^B charged in period 1, the rate R_2^B charged in period 2 to "relationship" firms that did not default in period 1, and the rate $\widehat{R}_2^B$ charged in period 2 to a new firm if a "relationship" firm defaulted, that will maximize Equation (3.5). The firms' participation constraints need to be fulfilled for all three loan rates.[64] The first order conditions are:

$$R_1^B = \bar{x} - c + \sigma - \beta(c - \tilde{c}) \left\{ 1 - \frac{1}{2} \frac{1}{\bar{x} - \underline{x}} (c + \tilde{c}) \right\} \tag{3.6}$$

$$R_2^B = \bar{x} - \tilde{c} \tag{3.7}$$

$$\widehat{R}_2^B = \bar{x} - c \tag{3.8}$$

where R_2^B and $\widehat{R}_2^B$ in Equation (3.6) are already replaced by Equations (3.7) and (3.8). Equation (3.7) denotes the loan rate charged in period 2 if a relationship is successfully formed from the first to the second period. This rate is higher compared to the rate charged by the capital market (Equation (3.4)) and is the

[64] The full maximization problem is shown in Appendix 3.E. As long as $c > 0$, $\tilde{c} > 0$, $c - \tilde{c} > 0$, and $2(\bar{x} - \underline{x}) > c + \tilde{c}$, the complementary slackness conditions imply that the participation constraints are not binding and all three Lagrange parameters equal zero.

reason why the bank tries to form a relationship in the first period. Equation (3.8) describes the case when the firm defaults in period 1 and the bank lends to a new firm in the second period. In such a situation, the bank charges the same rate as the capital market (Equation (3.4)), because the bank does not have more information about the new firm than the capital market. Equation (3.6) denotes the loan rate charged by the bank in period 1. Using Equation (3.3), Equation (3.6) can be written as:

$$R_1^B = R_1^C - \beta(c - \tilde{c}) \left\{ 1 - \frac{1}{2} \frac{1}{\bar{x} - \underline{x}} (c + \tilde{c}) \right\} \ .$$

The difference between the bank loan rate R_1^B and the lending rate on the capital market R_1^C equals the expected gain from the relationship – the difference between the monitoring cost for new firms c and relationship firms $\tilde{c}$. If the bank does not try to form a relationship, the degree of asymmetric information in the second period is the same for both the bank and the capital market ($\tilde{c} = c$) and the bank behaves like the capital market: an increase in uncertainty leads to an increase in the lending rate. However, if the bank decides to form a relationship with the borrower in order to reduce the monitoring costs, the bank charges a rate in period 1 that is lower than the rate demanded by the capital market. The larger the difference in monitoring costs, $c - \tilde{c}$, the lower is the bank loan rate relative to the capital market rate. Therefore, if the bank expects the benefits of a relationship to be relatively large, it cushions the effects of uncertainty on the firm's default probability by keeping the loan rate relatively low, thereby offsetting the increase in the probability of borrower default. The bank suffers (expected) losses in the first period, however, this is optimal for the bank because it increases the probability that the bank will be able to lend to the same firm in the next period. The bank can use its informational advantage in the second period and charge relatively high rates.

The model shows that the capital market increases its lending rate in response to an uncertainty event. By taking into account relationship lending, the model predicts that the larger the expected reduction in information asymmetries, the lower is the bank loan rate during periods of uncertainty.

3.4.3 Discussion: Compositional Changes and Collateral

Relationship lending is one explanation why capital market participants and banks respond differently to surprise increases in uncertainty. There could be other channels, for example the portfolio composition effect. Lenders could react to uncertainty shocks by shifting their portfolio from risky to less risky assets. Assume there are two types of borrowers: both types invest in risky projects. However, only one type is hit by the uncertainty shock – let us call it the “uncertain” type. The interest rate for (or the yield from) “uncertain” firms rises due to their increased probability of default, whereas the interest rate for (or the yield from) “certain” borrowers stays constant because this set of firms is not hit by the uncertainty shock and thus the risk premium does not move. What would we have to assume so that the risk-shifting channel explains decreases in bank loan rates and increases in corporate bond yields?

Looking at new loans or newly issued bonds, risk shifting leads lenders to extend less credit to the “uncertain” borrowers and more to firms with relatively certain project outcomes. The average loan rate of the newly formed bank portfolio falls only if the reduction in lending to “uncertain”-type borrowers is sufficiently large. In contrast, the average corporate bond yield increases if the capital market does not change its portfolio composition much. Therefore, purchases of corporate bonds from “uncertain”-type firms are not much reduced in uncertain times.[65] These two requirements have to be fulfilled so that the risk-shifting motive can explain both a decrease in the bank loan rate of new loans and an increase in the corporate bond yield of newly issued bonds.

When we look at outstanding amounts of loans or bonds, the risk-shifting motive is not applicable to explain the differences in the behavior of banks and capital markets. In this case, the composition of the aggregate bank (or market) portfolio cannot change. An increase in uncertainty raises the bank loan rate for (or the yield from) “uncertain”-type firms because of the higher risk of default. This increases the average loan rate (or the average yield), assuming that the interest rate that “certain”-type borrowers have to pay does not change (their default risk does not change). This is in contrast to the results from the fifth robustness test in which we find that loan rates on outstanding loans decrease in response to uncertainty shocks.

A second, and complementary, channel that could explain the different behavior of banks and the capital market is that banks can react to heightened uncertainty not only by changing lending rates, but also by changing non-price terms like collateral constraints. In the context of the risk channel of monetary policy this point is made, for example, by Afanasyeva and Güntner (2014). They argue that expansionary monetary policy leads banks to relax lending standards

[65] For a detailed exposition of these points, see Appendix 3.F.

such as collateral requirements for firms. Applied to the case of heightened uncertainty, banks react by tightening collateral requirements in exchange for not increasing lending rates. This does not present a pecuniary transfer from borrowers to lenders but does influence the risk sharing between the two parties (see Hainz and Wiegand, 2013). Banks are compensated for the higher default risk by being able to extract more collateral in case of borrower default. Capital markets do not have this instrument and can be compensated only by increasing interest rates. However, this channel would probably only explain why bank loan rates do not change in the face of heightened uncertainty, but not why they fall.

3.5 Conclusion

This paper makes four contributions to the field. First, using uncertainty proxies derived from survey data, we confirm that credit spreads increase in response to innovations in uncertainty, both in the United States and in Germany. Second, we find that uncertainty shocks increase credit spreads in market-based financial systems (measured by corporate bond yields) more than in bank-based systems (proxied by bank loan rates) due to increasing corporate bond yields, while bank loan rates decrease. Third, a standard DSGE model with CSV predicts increasing lending rates after surprise changes in uncertainty, which is consistent with the reaction of capital market participants. Fourth, we use a partial equilibrium model with CSV and relationship banking to explain the different behavior of capital markets and banks during uncertainty events. Taking into account relationship lending, the model predicts comparatively lower bank loan rates in a high-uncertainty environment. The larger the reduction in information asymmetries due the relationship, the lower is the loan rate.

The finding that credit spreads react less to heightened uncertainty in bank-based economies is important for economic decision makers. Recent studies argue that volatility/uncertainty is a determinant in the decision-making process of central bankers (see Bekaert, Hoerova, and Lo Duca, 2013, Jovanovic and Zimmermann, 2010, Kohlhas, 2011). Our analysis suggests that in bank-based systems the effects of uncertainty on credit spreads are dampened to a large extent by the banking system. If credit costs for firms do not increase much, uncertainty transmitted through the credit cost channel might be less of a concern for the conduct of monetary policy in bank-based systems. In the context of sticky prices, Bachmann, Born, Elstner, and Grimme (2013) find that increases in volatility have only small effects on the frequency of firms' price adjustments. They argue that traditional monetary policy aimed at stabilizing real output in uncertain times remains relatively effective. Our analysis introduces relationship banking as another factor why monetary policy does not have to react strongly to heightened uncertainty – at least in economies characterized by relationship lending.

Appendix

3.A Construction of Idiosyncratic Uncertainty Proxies

For Germany, we use the responses by manufacturing firms to the monthly IFO Business Climate Survey (IFO-BSC). The Business Climate Index, which is based on this survey, is a much-followed leading indicator for economic activity in Germany. We focus on the following question from the survey:

> Expectations for the next three months: Our domestic production activities with respect to product X will (without taking into account differences in the length of months or seasonal fluctuations) increase, roughly stay the same, decrease.

Exp_t^+ is defined as the fraction of firms that expect at time t an increase in production activity in the future and Exp_t^- as the fraction of firms that expect a decrease. Uncertainty is defined as the cross-sectional dispersion of expectations about future production:

$$FDISP_t^{GER} = \sqrt{Exp_t^+ + Exp_t^- - (Exp_t^+ - Exp_t^-)^2}\ . \tag{3.9}$$

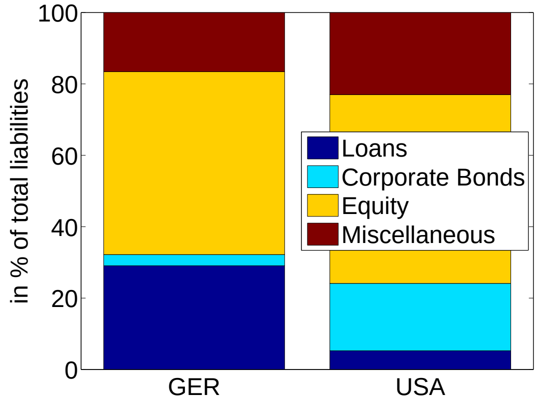
For the United States, we use data from the Business Outlook Survey (BOS), which is conducted on a monthly basis by the Federal Reserve Bank of Philadelphia and surveys manufacturing firms in the Third Fed district. We focus on the following question from the survey:

> General Business Conditions: What is your evaluation of the level of general business activity six months from now vs. [Current Month]: decrease, no change, increase?

In contrast to what is available for the IFO-BSC, we do not have access to detailed micro data from the BOS. However, the net balances Exp_t^+ and Exp_t^- are available. With the help of Equation (3.9), we calculate the U.S. uncertainty proxy, $FDISP^{US}$, as the dispersion of firms' forecasts about the general business outlook.

3.B Data

Figure 3.12: Liability Side of Nonfinancial Corporate Business



Notes: Data are from 2012 and collected from the respective national central banks.

Table 3.4: Data Sources: Germany

Variable	Description	Source
$FDISP^{GER}$	Cross-sectional standard deviation of production expectations, manufacturing firms, seasonally adjusted with X-12 and standardized	IFO & own calculations
Production	In manufacturing, seasonally adjusted, constant prices	Federal Statistical Office
Employment	In manufacturing, seasonally adjusted	Federal Statistical Office
Loan rate	Loan rate of loans other than revolving loans and overdrafts, new business, up to 1 year, in % p.a.	Bundesbank
Loan rate (outstanding)	Loan rate of loans other than revolving loans and overdrafts, outstanding amount, up to 1 year, in % p.a.	Bundesbank
Corp bond yield	Yields on fully taxed bonds outstanding, issued by non-financial corporations	Bundesbank
Government bond yield	1 to 2 years of maturity, in % p.a.	Bundesbank
EONIA	Day-to-day money market rate, monthly average, in % p.a.	Bundesbank
PPI	Producer prices of industrial products, seasonally adjusted	Federal Statistical Office

Table 3.5: Data Sources: United States

Variable	Description	Source
$FDISP^{US}$	Cross-sectional standard deviation of production expectations, manufacturing firms, third FED district, seasonally adjusted with X-12 and standardized	BOS & own calculations
Production	In manufacturing, seasonally adjusted, constant prices	Federal Reserve Board
Employment	In manufacturing, seasonally adjusted	BLS
Corporate bond yield	effective yield of investment grade rated corporate debt with maturity between 1 and 3 years	Merrill Lynch
Prime rate	Charged by commercial banks, used to price short-term business loans, in % p.a.	Federal Reserve Board
Loan rate	Charged by commercial banks for all commercial and industrial loans, up to 1 year, interpolated from quarterly to monthly frequency, shifted*, in % p.a.	Federal Reserve Board
Government bond yield 3y	3-year treasury bond yield	Federal Reserve Board
Government bond yield 1y	1-year treasury bond yield	Federal Reserve Board
Federal Funds Rate	Fed Funds Effective Rate	Federal Reserve Board
PPI	Producer prices, finished goods, seasonally adjusted	BLS

Notes: Shifted*: the monthly series is shifted by one month, because the original quarterly data is collected during the middle month of each quarter.

3.C Bayesian VAR Model

In this section we explain the Bayesian VAR (BVAR) estimation used in the section on robustness in the main text.

Consider the VAR(p) model:

$$Y_t = c + A_1 Y_{t-1} + \ldots + A_p Y_{t-p} + u_t \tag{3.10}$$

where Y_t is $n \times 1$ vector of endogenous variables, c is $n \times 1$ vector of constants, $A_1 \ldots A_p$ is a set of matrices of coefficients, u_t is $n \times 1$ vector of normally distributed residuals with covariance matrix Σ. Equation (3.10) can also be written as

$$Y = XB + U \tag{3.11}$$

where $Y = (Y_1, \ldots, Y_t)'$, $X = (X_1, \ldots, X_T)'$, $X_t = (Y'_{t-1}, \ldots, Y'_{t-p}, 1)'$, $B = (A_1, \ldots, A_p, c)'$ and $U = (u_1, \ldots, u_T)'$. Note that B contains all coefficients $k = n(np+1)$ of the model. In the following, we impose additional prior beliefs on the parameters through a variant of the Minnesota prior suggested by Litterman (1986). This prior captures the belief that variables characterized by high persistence can be reasonably described by a random walk with drift. The prior for variables that are believed to quickly revert to their respective mean is white noise. In addition, the prior implies that recent lags are believed to be more informative than more distant ones. The prior also incorporates the belief that own lags are more insightful for a given variable than lags of other variables.

Originally, Litterman (1986) assumes that the covariance matrix is diagonal. Allowing for correlation among residuals, however, is essential for structural analysis. Therefore, we follow Kadiyala and Karlsson (1997) and rely on a generalized version of the prior by imposing a normal inverted Wishart prior of the form:

$$\Sigma \sim IW\left(S_0, \alpha_0\right) \quad \text{and} \quad \text{vec}(B)|\Sigma \sim N\left(\text{vec}(B_0), \Sigma \otimes \Omega_0\right) \tag{3.12}$$

where the elements S_0, α_0, V_0, and Ω_0 are functions of hyperparameters, which reflect the prior beliefs. We follow Banbura, Giannone, and Reichlin (2010) and implement the prior (Equation (3.12)) by adding the following dummy observations to the original data:

$$Y_d = \begin{pmatrix} \mathrm{diag}(\delta_1\sigma_1, \ldots, \delta_n\sigma_n)/\lambda \\ 0_{n(p-1)\times n} \\ \mathrm{diag}(\sigma_1, \ldots, \sigma_n) \\ 0_{1\times n} \end{pmatrix}$$

$$X_d = \begin{pmatrix} \mathrm{diag}(1, 2, \ldots, p) \otimes \mathrm{diag}(\sigma_1, \ldots, \sigma_n)/\lambda & 0_{np\times 1} \\ 0_{n\times np} & 0_{n\times 1} \\ 0_{1\times np} & \epsilon \end{pmatrix}$$

The hyperparameters δ_i, σ_i, ϵ, and λ are set as following. δ_i is set to 1 if variable i is believed to be highly persistent, a value of 0 reflects the belief that the variable is characterized by strong mean reversion. σ_i accounts for the different scale and variability of the variables; it is set equal to the standard deviation of a residual from a univariate autoregression of variable i. The number of lags is set to 12; the sample period is the same as in the VAR. An uninformative prior is chosen for the intercepts; therefore, ϵ is set to a very small number (10^{-4}). λ characterizes the tightness of the prior distribution and determines the relative importance of the prior beliefs in the estimation. For $\lambda \to \infty$, the posterior expectations equal the OLS estimates and the prior is uninformative. For $\lambda \to 0$, the posterior equals the prior and the estimates are not influenced by the data.

The artificial data T_d are added to the original data T so that $T_* = T + T_d$. Adding the artificial data to the original VAR (Equation (3.11)) leads to

$$Y_* = X_* B + U_* \tag{3.13}$$

where $Y_* = (Y, Y_d)'$, $X_* = (X, X_d)'$, and $U_* = (U, U_d)'$. Banbura, Giannone, and Reichlin (2010) show that the posterior of the parameters is then a function of the hyperparameters:

$$\Sigma|Y \sim IW\left(\hat{\Sigma}, T+n+2\right) \quad \text{and} \quad \mathrm{vec}(B)|\Sigma, Y \sim N\left(\mathrm{vec}(\hat{B}), \Sigma \otimes (X_*' X_*)^{-1}\right)$$

where $\hat{\Sigma}$ and $\hat{B}$ are the covariance and the coefficients from an OLS regression of Y_* on X_*.[66]

The estimation procedure and the calculation of impulse responses is as following: First, we draw the covariance matrix $\tilde{\Sigma}$ from the inverted Wishart distribution and the corresponding vector of coefficients $\tilde{B}$ from the multivariate Normal distribution. Second, we compute the Cholesky decomposition. Third,

[66] For a forecast evaluation of different variants of the BVAR, see, e.g., Berg and Henzel (forthcoming).

we calculate impulse responses. Fourth, steps 1 to 3 are repeated 5,000 times. Finally, we calculate for each variable the median response and the 16th and 84th percentiles at each point in time.

The hyperparameter λ is calibrated to 0.25, which is in line with Banbura, Giannone, and Reichlin (2010), who set λ to 0.262 in a VAR with seven variables. The hyperparameters δ_i are set to 1 for the interest rate and production variables, reflecting the belief that these variables are better described as persistent rather than as white noise in the estimation period. For uncertainty, we set δ_i equal to 0, assuming that uncertainty quickly reverts to its mean.

3.D Detailed Description of the DSGE Model with Financial Frictions and Uncertainty Shocks

The Model

This section describes the DSGE model used in the main text. The model is very similar to the one outlined by Bernanke, Gertler, and Gilchrist (1999) with the addition of an explicit uncertainty process based on Fernández-Villaverde (2010). Variants of this setup can be found in Christiano, Motto, and Rostagno (2014), Cesa-Bianchi and Fernandez-Corugedo (2014), Chugh (2014), Dorofeenko, Lee, and Salyer (2008), Fendoglu (2014), Hafstead and Smith (2012).

Household

There is a representative household that maximizes utility by choosing real consumption C_t, nominal deposits D_t held at the bank, which pay the nominal interest rate R_t^N. In addition, the household provides labor H_t to firms, which pay a real wage W_t. T_t is the net transfer from ownership of the entrepreneurs. The household's utility and budget constraint are

$$\max_{\{C_t,H_t,D_t\}} \mathbb{E}_t \left[\sum_{t=0}^{+\infty} \beta^t \left\{ \frac{C_t^{1-\varrho}}{1-\varrho} - \chi \frac{H_t^{1+\varphi}}{1+\varphi} \right\} \right]$$

$$s.t.$$

$$C_t + \frac{D_t}{P_t} \leq W_t H_t + \frac{R_{t-1}^N}{\Pi_t} D_{t-1} + T_t$$

where $\Pi_t = P_t/P_{t-1}$ is the gross inflation rate and P_t is the aggregate price index. The first order conditions are

$$\begin{aligned} C_t^{-\varrho} &= \lambda_t \\ \lambda_t W_t &= \chi H_t^{\varphi} \\ \lambda_t &= \beta \mathbb{E}_t \left[\lambda_{t+1} \frac{R_t^N}{\Pi_{t+1}} \right] \end{aligned}$$

Final Good Producer

The representative final good producer assembles a final good Y_t by combining intermediate goods Y_{it} according to the Dixit-Stiglitz aggregator

$$Y_t = \left(\int_0^1 Y_{it}^{\frac{\epsilon-1}{\epsilon}} di \right)^{\frac{\epsilon}{\epsilon-1}}$$

where ϵ is the elasticity of substitution across goods. The final good producer maximizes profits, $P_t Y_t - \int_0^1 P_{it} Y_{it} di$, subject to the Dixit-Stiglitz aggregator, taking intermediate goods prices P_{it} and the final good price P_t as given. The demand for intermediate goods is:

$$Y_{it} = \left(\frac{P_{it}}{P_t} \right)^{-\epsilon} Y_t$$

where Y_t is aggregate demand and the price level equals $P_t = \left(\int_0^1 P_{it}^{1-\epsilon} di \right)^{\frac{1}{1-\epsilon}}$.

Intermediate Good Producers

The intermediate goods are produced by a continuum of monopolistically competitive firms. The intermediate goods producers combine labor and capital using a Cobb-Douglas production function to produce intermediate goods (production is, therefore, constant returns to scale)

$$Y_{it} = (K_{it-1})^{\alpha} H_{it}^{1-\alpha} \tag{3.14}$$

Capital is rented from entrepreneurs; labor is hired from households. Intermediate goods producers solve a two-stage problem. In the first stage, they minimize real costs, $W_t H_{it} + r_t^K K_{it-1}$, subject to Equation (3.14) and taking factor prices as given. r_t^K denotes the rental rate of capital. Cost minimization implies

$$K_{it-1} = \frac{\alpha}{1-\alpha} \frac{W_t}{r_t^K} H_{it}$$

Real marginal costs are:

$$MC_t = \left(\frac{1}{1-\alpha}\right)^{1-\alpha} \left(\frac{1}{\alpha}\right)^{\alpha} W_t^{1-\alpha} \left(r_t^K\right)^{\alpha}$$

In the second stage, intermediate goods producers choose the price, P_{it}, to maximize discounted real profits. Prices can be changed with probability $1-\theta$ in each period. The maximization problem of firm i is

$$\max_{P_{it}} \mathbb{E}_t \sum_{k=0}^{\infty} (\beta\theta)^k \frac{\lambda_{t+k}}{\lambda_t} \left[\left(\frac{P_{it}}{P_{t+k}} - MC_{t+k}\right) Y_{it+k}\right]$$
$$s.t.$$
$$Y_{it+k} = \left(\frac{P_{it}}{P_{t+k}}\right)^{-\epsilon} Y_{t+k}$$

Assuming a symmetric equilibrium, $P_{it}^* = P_t^*$, where P_{it}^* is the optimal price chosen by the intermediate goods producer i, results in the following equations:

$$\begin{aligned}
x_t^1 &= \frac{\epsilon-1}{\epsilon} x_t^2 \\
x_t^1 &= \lambda_t MC_t Y_t + \beta\theta \mathbb{E}_t (\Pi_{t+1})^{\epsilon} x_{t+1}^1 \\
x_t^2 &= \lambda_t \tilde{P}_t Y_t + \beta\theta \mathbb{E}_t (\Pi_{t+1})^{\epsilon-1} \left(\frac{\tilde{P}_t}{\tilde{P}_{t+1}}\right) x_{t+1}^2
\end{aligned}$$

where $\Pi_t = P_t / P_{t-1}$ and $\tilde{P}_t = P_t^* / P_t$. The aggregate price index evolves as

$$1 = \theta (\Pi_t)^{(\epsilon-1)} + (1-\theta)(\tilde{P}_t)^{1-\epsilon}$$

Capital Good Producer

The capital good producer buys the old non-depreciated capital stock $(1-\delta)K_{t-1}$ from entrepreneurs. The existing capital is combined with investment I_t to produce new capital K_t, which is sold to entrepreneurs at real price Q_t. The production of new capital induces transformation costs $\phi_k(I_t/K_{t-1})K_{t-1}$. Buying, producing, and selling capital all takes place within period t. The maximization problem of the capital good producer is

$$\max_{I_t} \; Q_t K_t - Q_t(1-\delta)K_{t-1} - I_t$$

subject to the law of motion for capital

$$K_t = (1-\delta)K_{t-1} + \phi_k\left(\frac{I_t}{K_{t-1}}\right)K_{t-1}.$$

The first-order condition equals

$$Q_t = \left[1 - \phi_k\left(\frac{I_t}{K_{t-1}} - \delta\right)\right]^{-1}$$

where $\phi_k(\frac{I_t}{K_{t-1}}) = \frac{I_t}{K_{t-1}} - \frac{\phi_k}{2}\left(\frac{I_t}{K_{t-1}} - \delta\right)^2$.

Entrepreneurs

Entrepreneur j buys K_t^j at price Q_t at the end of period t to be used for production in period $t+1$. He finances these purchases with his net worth N_t^j and real bank loans B_t^j:

$$Q_t K_t^j = B_t^j + N_t^j$$

The average real return of capital R_{t+1}^K depends on the real rental rate of capital r_{t+1}^K and the return from the non-depreciated capital stock, $(1-\delta)K_t$,

$$R_{t+1}^K = \frac{r_{t+1}^K + (1-\delta)Q_{t+1}}{Q_t}$$

At the beginning of period $t+1$, each entrepreneur j experiences an idiosyncratic shock ω_{t+1}^j that transforms capital into effective capital $\omega_{t+1}^j K_t^j$. The total ex-post return of entrepreneur j equals $\omega_{t+1}^j R_{t+1}^K Q_t K_t^j$. The shock ω_{t+1}^j is log-normally distributed across all entrepreneurs with a cumulative distribution function denoted by $F(\omega)$ and an expected value of unity. The mean and standard deviation of $\log \omega_{t+1}^j$ are $\mu_{\omega,t}$ and $\sigma_{\omega,t}$, respectively. Following Fernández-Villaverde (2010), idiosyncratic uncertainty $\sigma_{\omega,t}$ evolves as

$$\log \sigma_{\omega,t} = (1-\rho_\sigma)\log \sigma_\omega + \rho_\sigma \log \sigma_{\omega,t-1} + \eta_\sigma \epsilon_{\sigma,t}, \quad \epsilon_{\sigma,t} \sim N(0,1)$$

where σ_ω is the steady state value of uncertainty.

Following Bernanke, Gertler, and Gilchrist (1999), we assume an asymmetric information problem between borrowers and lenders. The idiosyncratic shock is private information to the entrepreneur; a bank can observe the shock only by paying a monitoring cost, which is a fraction μ of the realized total return on capital. The entrepreneur is able to repay his loan plus interest whenever his revenue, $\omega_{t+1}^j R_{t+1}^K Q_t K_t^j$, is larger than his debt, $Z_t^j B_t^j$, where Z^j is the loan rate faced by entrepreneur j. This is the case for all $\omega_{t+1}^j > \bar{\omega}_{t+1}^j$ where the threshold level $\bar{\omega}_{t+1}^j$ is the level at which the entrepreneur is just able to pay back the loan. This threshold value is determined in a contract between the entrepreneur and the bank. Therefore, there is a relationship between the loan rate Z^j and the threshold value $\bar{\omega}_{t+1}^j$

$$\bar{\omega}_{t+1}^j = \frac{Z_t^j B_t^j}{R_{t+1}^K Q_t K_t^j}$$

The entrepreneur defaults if $\omega_{t+1}^j < \bar{\omega}_{t+1}^j$; the bank monitors the entrepreneur and the share $(1-\mu)\omega_{t+1}^j R_{t+1}^K Q_t K_t^j$ is seized by the bank. Defaulting entrepreneurs receive nothing.

The debt contract between the entrepreneur and the bank is set up so that the lender receives an expected return equal to the riskless rate in all states of the world while maximizing the expected return to capital to entrepreneurs. This leads to a maximization problem for the entrepreneur, who chooses a schedule of threshold values $\bar{\omega}_{t+1}^j$ and the loan volume B_t^j to maximize his return

$$\max_{\bar{\omega}_{t+1}^j, B_t^j} \int_{\bar{\omega}_{t+1}^j}^{\infty} \omega dF(\omega) R_{t+1}^K Q_t K_t^j - [1 - F(\bar{\omega}_{t+1}^j)] Z_{t+1}^j B_t^j$$

where the first term denotes the average return of a project when $\omega_{t+1}^j > \bar{\omega}_{t+1}^j$. The second term describes the probability of loan repayment. The entrepreneur needs to take into account the zero profit condition of the bank, which has to hold in all states of the world

$$[1 - F(\bar{\omega}_{t+1}^j) Z_{t+1}^j B_t^j + (1-\mu) \int_0^{\bar{\omega}_{t+1}^j} \omega dF(\omega) R_{t+1}^K Q_t K_t^j = R_t B_t^j \tag{3.15}$$

where R_t is the (non-contingent) return of households with savings at the bank. The first term on the left-hand side is the return if the loan is paid back; the second term describes the revenue if the loan defaults. On the right-hand side is the cost of funds, which is what the bank has to earn in each state of the world to be able to repay back the household depositors.

This gives rise to a function that relates the (expected) external finance premium (EFP), $\mathbb{E}_t R^K_{t+1}/R_t$, to the net-worth-to-capital ratio $N^j_t/Q_t K^j_t$

$$\mathbb{E}_t \frac{R^K_{t+1}}{R_t} \left[1 - \Gamma(\bar{\omega}_{t+1})\right] = \mathbb{E}_t \lambda^b_t(\bar{\omega}_{t+1}) \frac{N^j_t}{Q_t K^j_t}$$

where $\mathbb{E}_t \left[1 - \Gamma(\bar{\omega}_{t+1})\right]$ is the expected share of total profits going to the entrepreneur[67] and $\lambda^b_t(\bar{\omega}_{t+1})$ denotes the Lagrange multiplier of the zero profit condition and equals

$$\lambda^b_t(\bar{\omega}_{t+1}) = \frac{\Gamma_\omega(\bar{\omega}_{t+1})}{\Gamma_\omega(\bar{\omega}_{t+1}) - \mu G_\omega(\bar{\omega}_{t+1})}$$

Bernanke, Gertler, and Gilchrist (1999) point out that the assumption of constant returns to scale in production leads to a linear relationship between N^j_t and K^j_t at the firm level and does not depend on idiosyncratic factors. This facilitates aggregation enormously because it is not necessary to keep track of the distribution over net worth.

To make sure that entrepreneurs do not accumulate enough net worth to finance all projects on their own, we assume that an exogenous fraction $(1 - \gamma^e)$ of entrepreneurs' share of profits is consumed in each period. Aggregate entrepreneurial consumption equals

$$C^e_t = (1 - \gamma^e) \left[1 - \Gamma(\bar{\omega}_t)\right] R^K_t Q_{t-1} K_{t-1}$$

while aggregate net worth N_t evolves as

$$N_t = \gamma^e \left[1 - \Gamma(\bar{\omega}_t)\right] R^K_t Q_{t-1} K_{t-1}.$$

Bank

The representative bank intermediates funds between households and entrepreneurs. It provides real loans B_t at rate Z_t to entrepreneurs. Households receive a (non-contingent) nominal rate R^N_t for their deposits D_t. The balance sheet of the bank is: $L_t = D_t$.

[67] $\mathbb{E}_t \left[1 - \Gamma(\bar{\omega}_{t+1})\right]$ equals $\int_{\bar{\omega}^j_{t+1}}^{\infty} \omega dF(\omega) R^K_{t+1} Q_t K^j_t - [1 - F(\bar{\omega}^j_{t+1})] Z^j_{t+1} B^j_t$. The zero profit condition of the bank (Equation (3.15)) can then be rewritten as $\frac{R^K_{t+1}}{R_t}[\Gamma(\bar{\omega}_{t+1}) - \mu G(\bar{\omega}_{t+1})] = \frac{B_t}{Q_t K_t}$, where $G(\bar{\omega}_{t+1}) = \int_0^{\bar{\omega}^j_{t+1}} \omega dF(\omega)$.

Monetary Policy and Market Clearing

The central bank sets the nominal interest rate R_t^N according to a Taylor rule:

$$\frac{R_t^N}{R^N} = \left(\frac{R_{t-1}^N}{R^N}\right)^{\gamma_r} \left[\left(\frac{\Pi_t}{\Pi}\right)^{\gamma_\pi} \left(\frac{Y_t}{Y_{t-1}}\right)^{\gamma_y}\right]^{(1-\gamma_r)}$$

where $R_t = \mathbb{E}_t \left(R_t^N/\Pi_{t+1}\right)$, R^N is the steady state nominal interest rate, Π is the steady state inflation rate, γ_r generates interest-rate smoothing, and γ_π and γ_y control the response of the interest rate to deviations from steady state inflation and steady state output.

The model is closed by the market clearing condition in the goods market

$$Y_t = C_t + C_t^e + I_t + \mu G(\bar{\omega}_t) R_t^k Q_{t-1} K_{t-1}$$

where $\mu G(\bar{\omega}_t) R_t^k Q_{t-1} K_{t-1}$ denotes aggregate monitoring cost. The average productivity of defaulting firms, $G(\bar{\omega}_t)$, equals $\int_0^{\bar{\omega}_t^j} \omega dF(\omega)$.

Equilibrium conditions

Household

$$\begin{aligned} C_t^{-\varrho} &= \lambda_t \\ \lambda_t W_t &= \chi H_t^{\varphi} \\ \lambda_t &= \beta \mathbb{E}_t \left[\lambda_{t+1} \frac{R_t^N}{\Pi_{t+1}}\right] \end{aligned}$$

Capital Good Producer

$$\begin{aligned} Q_t &= \left[1 - \phi_k \left(\frac{I_t}{K_{t-1}} - \delta\right)\right]^{-1} \\ K_t &= (1-\delta)K_{t-1} + K_{t-1}\left[\frac{I_t}{K_{t-1}} - \frac{\phi_k}{2}\left(\frac{I_t}{K_{t-1}} - \delta\right)^2\right] \end{aligned}$$

Price index

$$1 = \theta(\Pi_t)^{(\epsilon-1)} + (1-\theta)(\tilde{P}_t)^{1-\epsilon}$$

Intermediate Firms

$$
\begin{aligned}
x_t^1 &= \frac{\epsilon - 1}{\epsilon} x_t^2 \\
x_t^1 &= \lambda_t MC_t Y_t + \beta\theta \mathbb{E}_t (\Pi_{t+1})^{\epsilon} x_{t+1}^1 \\
x_t^2 &= \lambda_t \tilde{P}_t Y_t + \beta\theta \mathbb{E}_t (\Pi_{t+1})^{\epsilon-1} \left(\frac{\tilde{P}_t}{\tilde{P}_{t+1}} \right) x_{t+1}^2 \\
K_{t-1} &= \frac{\alpha}{1-\alpha} \frac{W_t}{r_t^K} H_t \\
MC_t &= \left(\frac{1}{1-\alpha} \right)^{(1-\alpha)} \left(\frac{1}{\alpha} \right)^{\alpha} W_t^{1-\alpha} \left(r_t^K \right)^{\alpha} \\
Y_t &= K_{t-1}^{\alpha} H_t^{1-\alpha}
\end{aligned}
$$

Entrepreneurs

$$
\begin{aligned}
B_t &= Q_t K_t - N_t \\
R_t^K &= \left[\frac{r_t^K + (1-\delta) Q_t}{Q_{t-1}} \right] \\
\frac{R_{t+1}^K}{R_t} \left[\Gamma(\bar{\omega}_{t+1}) - \mu G(\bar{\omega}_{t+1}) \right] &= \frac{B_t}{Q_t K_t} \\
\mathbb{E}_t \frac{R_{t+1}^K}{R_t} \left[1 - \Gamma(\bar{\omega}_{t+1}) \right] &= \mathbb{E}_t \lambda_t^b(\bar{\omega}_{t+1}) \frac{N_t}{Q_t K_t} \\
\lambda_t^b(\bar{\omega}_{t+1}) &= \frac{\Gamma'(\bar{\omega}_{t+1})}{\Gamma'(\bar{\omega}_{t+1}) - \mu G'(\bar{\omega}_{t+1})} \\
N_t &= \gamma_e \left[1 - \Gamma(\bar{\omega}_t) \right] R_t^K Q_{t-1} K_{t-1} \\
C_t^E &= (1-\gamma_e) \left[1 - \Gamma(\bar{\omega}_t) \right] R_t^K Q_{t-1} K_{t-1}
\end{aligned}
$$

Monetary Policy and Market Clearing

$$
\begin{aligned}
\frac{R_t^N}{R^N} &= \left(\frac{R_{t-1}^N}{R^N} \right)^{\gamma_r} \left[\left(\frac{\Pi_t}{\Pi} \right)^{\gamma_\pi} \left(\frac{Y_t}{Y_{t-1}} \right)^{\gamma_y} \right]^{(1-\gamma_r)} \\
R_t &= \mathbb{E}_t \frac{R_t^N}{\Pi_{t+1}} \\
Y_t &= C_t + C_t^e + I_t + \mu G(\bar{\omega}_t) R_t^k Q_{t-1} K_{t-1}
\end{aligned}
$$

Uncertainty Shock Process

$$
\log \sigma_{\omega,t} = (1-\rho_\sigma) \log \sigma_\omega + \rho_\sigma \log \sigma_{\omega,t-1} + \eta_\sigma \epsilon_{\sigma,t}
$$

Miscellaneous

$$
\begin{aligned}
F(\bar{\omega}_t) &= \Phi\left(\frac{0.5\sigma_{\omega_{t-1}} + \log(\bar{\omega}_t)}{\sigma_{\omega_{t-1}}}\right) \\
G(\bar{\omega}_t) &= \Phi\left(\frac{0.5\sigma_{\omega_{t-1}} + \log(\bar{\omega}_t)}{\sigma_{\omega_{t-1}}} - \sigma_{\omega_{t-1}}\right) \\
\Gamma(\bar{\omega}_t) &= \bar{\omega}_t\left[1 - F(\bar{\omega}_t)\right] + G(\bar{\omega}_t) \\
\Gamma'(\bar{\omega}_{t+1}) &= 1 - F(\bar{\omega}_{t+1}) \\
G'(\bar{\omega}_{t+1}) &= \bar{\omega}_{t+1} \times F'(\bar{\omega}_{t+1}, \sigma_{\omega,t}) \\
F'(\bar{\omega}_{t+1}) &= \phi\left(\frac{0.5\sigma_{\omega_t} + \log(\bar{\omega}_{t+1})}{\sigma_{\omega_t}}\right)\frac{\sigma_{\omega_t}}{\bar{\omega}_{t+1}} \\
EFP_t &= \mathbb{E}_t \frac{R^K_{t+1}}{R_t} \\
spread_t &= \bar{\omega}_t \, \frac{R^K_t}{R_{t-1}} \, \frac{Q_{t-1}K_{t-1}}{B_{t-1}} \\
R^B_t &= \bar{\omega}_t \, R^K_t \, \frac{Q_{t-1}K_{t-1}}{B_{t-1}} \, \mathbb{E}_t\Pi_{t+1} \\
lev_t &= \frac{Q_t K_t}{N_t}
\end{aligned}
$$

where $\Phi(\cdot)$ is the standard normal cdf and $\phi(\cdot)$ is the standard normal pdf. $F(\bar{\omega}_t)$ is the default rate, EFP_t is the expected external finance premium, $spread_t$ denotes the ratio of the loan rate to the riskless real rate, R^B_t is the loan rate, and lev_t denotes leverage.

3.E Maximization Problem of Relationship Bank during Uncertainty Event

The expected return of the bank subject to the firm's participation constraints is

$$\int_{\underline{x}-\sigma}^{R_1^B}(x-c)\frac{1}{(\bar{x}+\sigma)-(\underline{x}-\sigma)}dx+\int_{R_1^B}^{\bar{x}+\sigma}R_1^B\frac{1}{(\bar{x}+\sigma)-(\underline{x}-\sigma)}dx$$

$$+\lambda_1^B\left\{\int_{R_1^B}^{\bar{x}+\sigma}(x-R_1^B)\frac{1}{(\bar{x}+\sigma)-(\underline{x}-\sigma)}dx-0\right\}$$

$$+\beta\left\{1-\int_{\underline{x}-\sigma}^{R_1^B}\frac{1}{(\bar{x}+\sigma)-(\underline{x}-\sigma)}dx\right\}$$

$$\left\{\int_{\underline{x}}^{R_2^B}(x-\tilde{c})\frac{1}{\bar{x}-\underline{x}}dx+\int_{R_2^B}^{\bar{x}}R_2^B\frac{1}{\bar{x}-\underline{x}}dx+\lambda_2^B\left[\int_{R_2^B}^{\bar{x}}(x-R_2^B)\frac{1}{\bar{x}-\underline{x}}dx-0\right]\right\}$$

$$+\beta\left\{\int_{\underline{x}-\sigma}^{R_1^B}\frac{1}{(\bar{x}+\sigma)-(\underline{x}-\sigma)}dx\right\}$$

$$\left\{\int_{\underline{x}}^{\widehat{R}_2^B}(x-c)\frac{1}{\bar{x}-\underline{x}}dx+\int_{\widehat{R}_2^B}^{\bar{x}}\widehat{R}_2^B\frac{1}{\bar{x}-\underline{x}}dx+\widehat{\lambda}_2^B\left[\int_{\widehat{R}_2^B}^{\bar{x}}(x-\widehat{R}_2^B)\frac{1}{\bar{x}-\underline{x}}dx-0\right]\right\}\ .$$

The resulting FOCs are

$$R_1^B=\bar{x}-\frac{1}{1-\lambda_1^B}c+\sigma-\beta\frac{1}{1-\lambda_1^B}\left\{(c-\tilde{c})-\frac{1}{2}\frac{1}{\bar{x}-\underline{x}}\left[\frac{1}{1-\widehat{\lambda}_2^B}c^2+\frac{1}{1-\lambda_2^B}\tilde{c}^2\right]\right\}$$

$$R_2^B=\bar{x}-\frac{1}{1-\lambda_2^B}\tilde{c}$$

$$\widehat{R}_2^B=\bar{x}-\frac{1}{1-\widehat{\lambda}_2^B}c\ .$$

3.F Risk Shifting Motive

We assume there are two types of firms. Banks as well as the capital market fund the two types. Both type of firms invest in risky projects. However, only one type is hit by an uncertainty shock, which we denote in the following as the "uncertain" type. Due to an asymmetric information problem between borrowers and lenders, the interest rate r_u^i, which "uncertain"-type firms have to pay, increases, therefore $\partial r_u^i(\sigma)/\partial\sigma > 0$. i denotes either the banking sector (B) or the capital market (CM). The interest rate of credit to (or the yield on bonds from) firms that are "not uncertain" r_{nu} stays constant because they are not hit by the uncertainty shock and, thus, their default probability and their risk premium does not change.

New Loans or Newly Issued Bonds Risk shifting means that lenders reduce their exposure to "uncertain"-type firms and increase lending to firms that are "not uncertain". Therefore, the amount of lending extended to the "uncertain" type x_u^i decreases, $\partial x_u^i(\sigma)/\partial\sigma < 0$, while the volume of lending given to "not uncertain" firms x_{nu}^i increases, $\partial x_{nu}^i(\sigma)/\partial\sigma > 0$. The average (weighted) interest rate (or yield) r^i equals

$$r^i = \frac{1}{x_{nu}^i(\sigma) + x_u^i(\sigma)} \left\{ x_{nu}^i\left(\sigma\right) r_{nu} + x_u^i\left(\sigma\right) r_u^i\left(\sigma\right) \right\} \ . \tag{3.16}$$

Assuming that the total amount of credit/bonds stays constant, $x_u^i(\sigma)+x_{nu}^i(\sigma) = x$, Equation (3.16) becomes

$$r^i = c \left\{ \left[x - x_u^i\left(\sigma\right)\right] r_{nu} + x_u^i\left(\sigma\right) r_u^i\left(\sigma\right) \right\}$$

where $c \equiv \frac{1}{x_{nu}^i + x_u^i}$ is a constant.

Taking the derivative of the average interest rate (yield) r^i with respect to uncertainty σ leads to

$$\frac{\partial r^i}{\partial\sigma} = c \left[\underbrace{\frac{\partial x_u^i}{\partial\sigma}}_{<0} \left(r_u^i - r_{nu}^i\right) + x_u^i \underbrace{\frac{\partial r_u^i}{\partial\sigma}}_{>0} \right] \ .$$

To use the risk-shifting motive as an explanation for decreasing loan rates and increasing corporate bond yields, two requirements must be met. For the bank $\frac{\partial r^B}{\partial\sigma} < 0$ has to hold – that is, the average interest rate on new loans r^B has to decrease following an increase in uncertainty σ. This can only be achieved if the reduction in lending to uncertain firms is relatively large (the reduction in lending is counteracted by the increase in the loan rate to these firms, r_u^B, thus, the drop in x_u^B needs to be sufficiently large). Therefore, banks need to carry out relatively large shifts in their portfolio composition in uncertain times.

In contrast, for the corporate bond market $\frac{\partial r^{CM}}{\partial \sigma} > 0$ has to hold, implying that capital markets need to reduce their purchases of bonds from "uncertain" firms much less than banks do decrease their loans. Therefore, the average yield on bonds only increases if the capital market hardly changes its portfolio composition in periods of uncertainty.

These two conditions must be fulfilled before risk shifting can explain both a decrease in the average bank loan rate and an increase in the average bond yield. The different behavior of banks and capital markets would then be explained by different credit supply elasticities in the two markets.

Outstanding Amounts of Loans or Bonds Looking at outstanding amounts instead of new loans or newly issued bonds, Equation (3.16) becomes:

$$r^i = \frac{1}{\bar{x}_{nu}^i + \bar{x}_u^i} \left\{ \bar{x}_{nu}^i r_{nu} + \bar{x}_u^i r_u^i (\sigma) \right\}$$

where $\bar{x}_{nu}^i$ and $\bar{x}_u^i$ imply that the loan and the bond volume are fixed, respectively. Individual banks or capital market participants are able to make shifts in their portfolio composition, at the aggregate level, however, the outstanding amounts cannot change. Taking the derivative of the average interest rate (yield) r^i with respect to uncertainty σ leads to

$$\frac{\partial r^i}{\partial \sigma} = c \left[\bar{x}_u^i \underbrace{\frac{\partial r_u^i}{\partial \sigma}}_{>0} \right] .$$

The bank loan rate of loans to (or the yield on bonds from) "uncertain" firms always increases, implying that the average loan rate (yield) r^i always increases. Therefore, for outstanding amounts the argument of risk-shifting is not applicable to explain the different behavior in loan rates and bond yields.

References

Afanasyeva, E., and J. Güntner (2014): "Lending Standards, Credit Booms and Monetary Policy," IMFS Working Paper No. 85, Goethe University Frankfurt.

Arellano, C., Y. Bai, and P. J. Kehoe (2012): "Financial Frictions and Fluctuations in Volatility," Staff Report No. 466, Federal Reserve Bank of Minneapolis.

Bachmann, R., and C. Bayer (2013): ""Wait-and-See" Business Cycles?," *Journal of Monetary Economics*, 60(6), 704–719.

——— (2014): "Investment Dispersion and the Business Cycle," *American Economic Review*, 104(4), 1392–1416.

Bachmann, R., B. Born, S. Elstner, and C. Grimme (2013): "Time-Varying Business Volatility, Price Setting, and the Real Effects of Monetary Policy," CEPR Discussion Paper No. 9702.

Bachmann, R., and S. Elstner (2013): "Firms' Optimism and Pessimism," NBER Working Paper No. 18989.

Bachmann, R., S. Elstner, and E. R. Sims (2013): "Uncertainty and Economic Activity: Evidence from Business Survey Data," *American Economic Journal: Macroeconomics*, 5(2), 217–249.

Baker, S., N. Bloom, and S. Davis (2013): "Measuring Economic Policy Uncertainty," Mimeo, Stanford University.

Baley, I., and J. A. Blanco (2013): "Learning To Price," Mimeo, New York University.

Ball, L. (1992): "Why does high inflation raise inflation uncertainty?," *Journal of Monetary Economics*, 29(3), 371–388.

Ball, L., and S. G. Cecchetti (1990): "Inflation and uncertainty at short and long horizons," *Brooking Papers on Economic Activity*, 21(1), 215–254.

Banbura, M., D. Giannone, and L. Reichlin (2010): "Large Bayesian Vector Auto Regressions," *Journal of Applied Econometrics*, 25(1), 71–292.

Barsky, R. B., and E. R. Sims (2012): "Information, Animal Spirits, and the Meaning of Innovations in Consumer Confidence," *American Economic Review*, 102(4), 1343–77.

Batchelor, R., and P. Dua (1993): "Survey vs ARCH measures of inflation uncertainty," *Oxford Bulletin of Economics and Statistics*, 55(3), 341–353.

——— (1996): "Empirical measures of inflation uncertainty: A cautionary note," *Applied Economics*, 28(3), 333–341.

Becker, S., and K. Wohlrabe (2008): "Micro Data at the Ifo Institute for Economic Research - The 'Ifo Business Survey' Usage and Access," *Journal of Applied Social Science Studies*, 128(2), 307–319.

Bekaert, G., M. Hoerova, and M. Lo Duca (2013): "Risk, Uncertainty and Monetary Policy," *Journal of Monetary Economics*, 60(7), 771–788.

Berg, T. O., and S. R. Henzel (forthcoming): "Point and Density Forecasts for the Euro Area Using Bayesian VARs," *International Journal of Forecasting*.

Berger, A. N., and G. F. Udell (1992): "Some Evidence on the Empirical Significance of Credit Rationing," *The Journal of Political Economy*, 100(5), 1047–1077.

Berger, D., and J. Vavra (2011): "Dynamics of the U.S. Price Distribution," Mimeo, Yale University.

Bernanke, B. (1983): "Irreversibility, Uncertainty, and Cyclical Investment," *The Quarterly Journal of Economics*, 98(1), 85–106.

Bernanke, B., M. Gertler, and S. Gilchrist (1999): "The Financial Accelerator in a Quantitative Business Cycle Framework," in *Handbook of Macroeconomics*, ed. by J. Taylor, and M. Woodford, vol. 1, chap. 21, pp. 1341–1393. Elsevier.

Bernanke, B., and F. S. Mishkin (1997): "Inflation targeting: A new framework for monetary policy?," *Journal of Economic Perspectives*, 11(2), 97–116.

Berument, H., and N. N. Dincer (2005): "Inflation and inflation uncertainty in the G7 countries," *Physica A: Statistical Mechanics and its Applications*, 348(C), 371–379.

Berument, H., Z. Kilinc, and U. Ozlale (2005): "The missing link between inflation uncertainty and interest rates," *Scottish Journal of Political Economy*, 52(2), 222–241.

Bhar, R., and S. Hamori (2004): "The link between inflation and inflation uncertainty: Evidence from G7 countries," *Empirical Economics*, 29(4), 825–853.

Blanchard, O. (2009): "(Nearly) nothing to fear but fear itself," *The Economist*, Jan 29th.

Bloom, N. (2009): "The Impact of Uncertainty Shocks," *Econometrica*, 77(3), 623–686.

Bloom, N., M. Floetotto, N. Jaimovich, I. Saporta-Eksten, and S. J. Terry (2012): "Really Uncertain Business Cycles," NBER Working Paper No. 18245.

Boivin, J., M. P. Giannoni, and I. Mihov (2009): "Sticky Prices and Monetary Policy: Evidence from Disaggregated US Data," *American Economic Review*, 99(1), 350–384.

Bomberger, W. A. (1996): "Disagreement as a measure of uncertainty," *Journal of Money, Credit and Banking*, 28(3), 381–392.

——— (1999): "Disagreement and uncertainty - A reply to Rich and Butler (1998)," *Journal of Money, Credit and Banking*, 31(2), 273–276.

Bomberger, W. A., and W. J. Frazer (1981): "Interest rates, uncertainty and the Livingston data," *Journal of Finance*, 36(3), 661–675.

Bonciani, D., and B. van Roye (2013): "Uncertainty shocks, banking frictions and economic activity," Kiel Working Paper No. 1843.

Boot, A. (2000): "Relationship Banking: What Do We Know?," *Journal of Financial Intermediation*, 9(1), 7–25.

Boot, A., and A. Thakor (2010): "The Accelerating Integration of Banks and Markets and its Implications for Regulation," in *The Oxford Handbook of Banking*, ed. by A. Berger, P. Molyneux, and J. Wilson, pp. 58–90. Oxford: Oxford University Press.

Born, B., S. Breuer, and S. Elstner (2014): "Uncertainty and the Great Recession," Working Paper 04/2014, German Council of Economic Experts, Wiesbaden.

Born, B., and J. Pfeifer (2014): "Policy Risk and the Business Cycle," *Journal of Monetary Economics*, 68(Nov), 68–85.

Brady, T. F., W. B. English, and W. R. Nelson (1998): "Recent Changes to the Federal Reserve's Survey of Terms of Business Lending," *Federal Reserve Bulletin*, 84, 604–615.

Brainard, W. (1967): "Uncertainty and the Effectiveness of Policy," *American Economic Review*, 57(2), 411–425.

Brunner, A. D., and G. D. Hess (1993): "Are higher levels of inflation less predictable? A state-dependent conditional heteroskedasticity approach," *Journal of the American Statistical Association*, 11(2), 187–197.

Bundesbank, D. (2004): "The new MFI interest rate statistics - methodology for collecting the German data," *Monthly Report*, January, 45–59.

Calvo, G. A. (1983): "Staggered Prices in a Utility-Maximizing Framework," *Journal of Monetary Economics*, 12(3), 383–398.

Caporale, G. M., and A. Kontonikas (2009): "The Euro and inflation uncertainty in the European Monetary Union," *Journal of International Money and Finance*, 28(6), 954–971.

Caporale, G. M., L. Onorante, and P. Paesani (2012): "Inflation and inflation uncertainty in the euro area," *Empirical Economics*, 43(2), 597–615.

Cesa-Bianchi, A., and E. Fernandez-Corugedo (2014): "Uncertainty in a model with credit frictions," Bank of England Working Paper No. 496.

Chang, K.-L., and C.-W. He (2010): "Does the magnitude of the effect of inflation uncertainty on output growth depend on the level of inflation?," *The Manchester School*, 78(2), 126–148.

Christiano, L., R. Motto, and M. Rostagno (2010): "Financial Factors in Economic Fluctuations," ECB Working Paper No. 1192.

——— (2014): "Risk Shocks," *American Economic Review*, 104(1), 27–65.

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

Chua, C. L., D. Kim, and S. Suardi (2011): "Are empirical measures of macroeconomic uncertainty alike?," *Journal of Economic Surveys*, 25(4), 801–827.

Chugh, S. K. (2014): "Firm Risk and Leverage-Based Business Cycles," Mimeo, Boston College.

Clark, T. E. (2009): "Is the Great Moderation over? An empirical analysis," *Federal Reserve Bank of Kansas City Economic Review*, Q IV, 5–42.

Comin, D., and S. Mulani (2006): "Diverging Trends in Aggregate and Firm Volatility," *The Review of Economics and Statistics*, 88(2), 374–383.

Cosimano, T. F., and D. W. Jansen (1988): "Estimates of the variance of U.S. inflation based upon the ARCH model: Comment," *Journal of Money, Credit and Banking*, 20(3), 409–421.

Cukierman, A., and A. H. Meltzer (1986): "A theory of ambiguity, credibility, and inflation under discretion and asymmetric information," *Econometrica*, 54(5), 1099–1128.

Cukierman, A., and P. Wachtel (1982): "Relative price variability and nonuniform inflationary expectations," *Journal of Political Economy*, 90(1), 146–157.

D'Amico, S., and A. Orphanides (2008): "Uncertainty and disagreement in economic forecasting," Finance and Economics Discussion Series No. 2008-56, Board of Governors of the Federal Reserve System.

Davis, G. K., and B. E. Kanago (2000): "The level and uncertainty of inflation: Results from OECD forecasts," *Economic Inquiry*, 38(1), 58–72.

Davis, S. J., and J. C. Haltiwanger (1992): "Gross Job Creation, Gross Job Destruction, and Employment Reallocation," *The Quarterly Journal of Economics*, 107(3), 819–863.

Davis, S. J., J. C. Haltiwanger, R. Jarmin, and J. Miranda (2006): "Volatility and Dispersion in Business Growth Rates: Publicly Traded and Privately Held Firms," *NBER Macroeconomics Annual*.

De Fiore, F., and H. Uhlig (2011): "Bank Finance versus Bond Finance," *Journal of Money, Credit and Banking*, 43(7), 1399–1421.

Diamond, D. W. (1984): "Financial Intermediation and Delegated Monitoring," *The Review of Economic Studies*, 51(3), 393–414.

Doms, M., and T. Dunne (1998): "Capital Adjustment Patterns in Manufacturing Plants," *Review of Economic Dynamics*, 1(2), 409–429.

Döpke, J., and U. Fritsche (2006): "When do forecasters disagree? An assessment of German growth and inflation forecast dispersion," *International Journal of Forecasting*, 22(1), 125–135.

Dorofeenko, V., G. S. Lee, and K. D. Salyer (2008): "Time-Varying Uncertainty and the Credit Channel," *Bulletin of Economic Research*, 60(4), 375–403.

Dovern, J., U. Fritsche, and J. Slacalek (2012): "Disagreement among forecasters in G7 countries," *Review of Economics and Statistics*, 94(4), 1081–1096.

Dovern, J., and J. Weisser (2011): "Accuracy, unbiasedness and efficiency of professional macroeconomic forecasts: An empirical comparison for the G7," *International Journal of Forecasting*, 27(2), 452–465.

Draghi, M. (2014): "Unemployment in the euro area," Speech at the annual central bank symposium in Jackson Hole.

Elder, J. (2004): "Another perspective on the effects of inflation uncertainty," *Journal of Money, Credit, and Banking*, 36(5), 911–928.

Engle, R. (1983): "Estimates of the variance of U.S. inflation based on the ARCH model," *Journal of Money, Credit and Banking*, 15(3), 286–301.

Evans, M. (1991): "Discovering the link between inflation rates and inflation uncertainty," *Journal of Money, Credit and Banking*, 23(2), 169–184.

Evans, M., and P. Wachtel (1993): "Inflation regimes and the sources of inflation uncertainty," *Journal of Money, Credit and Banking*, 25(3), 475–511.

Fama, E. (1985): "What's Different about Banks?," *Journal of Monetary Economics*, 15(1), 29–39.

Fendoglu, S. (2014): "Optimal Monetary Policy Rulse, Financial Amplification, and Uncertain Business Cycles," *Journal of Economic Dynamics and Control*, 46(C), 271–305.

Fernández-Villaverde, J. (2010): "Fiscal Policy in a Model With Financial Frictions," *American Economic Review: Papers & Proceedings*, 100(2), 35–40.

Fernández-Villaverde, J., P. Guerrón-Quintana, J. F. Rubio-Ramírez, and M. Uribe (2011): "Risk Matters: The Real Effects of Volatility Shocks," *American Economic Review*, 101(6), 2530–2561.

Fernández-Villaverde, J., P. A. Guerrón-Quintana, K. Kuester, and J. Rubio-Ramírez (2012): "Fiscal Volatility Shocks and Economic Activity," Mimeo, University of Pennsylvania.

Fernández-Villaverde, J., P. A. Guerrón-Quintana, and J. Rubio-Ramírez (2010): "Fortune or Virtue: Time-Variant Volatilities Versus Parameter Drifting in U.S. Data," NBER Working Paper No. 15928.

Fountas, S., and M. Karanasos (2007): "Inflation, output growth, and nominal and real uncertainty: Empirical evidence for the G7," *Journal of International Money and Finance*, 26(2), 229–250.

Friedman, M. (1977): "Nobel lecture: Inflation and unemployment," *Journal of Political Economy*, 85(3), 451–472.

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

Gerali, A., S. Neri, luca Sessa, and F. M. Signoretti (2010): "Credit and Banking in a DSGE Model of the Euro Area," *Journal of Money, Credit and Banking*, 42(6), 107–141.

Gilchrist, S., J. Sim, and E. Zakrajsek (2014): "Uncertainty, Financial Frictions, and Investment Dynamics," NBER Working Paper No. 20038.

Giordani, P., and P. Söderlind (2003): "Inflation forecast uncertainty," *European Economic Review*, 47(6), 1037–1059.

Golosov, M., and R. E. Lucas (2007): "Menu Costs and Phillips Curves," *Journal of Political Economy*, 115(2), 171–199.

Greenbaum, S. I., G. Kanatas, and I. Venezia (1989): "Equilibrium Loan Pricing under the Bank-Client Relationship," *Journal of Banking and Finance*, 13(2), 221–235.

Grier, K. B., O. T. Henry, N. Olekalns, and K. Shields (2004): "The asymmetric effects of uncertainty on inflation and output growth," *Journal of Applied Econometrics*, 19(5), 551–565.

Grier, K. B., and M. J. Perry (1996): "Inflation, inflation uncertainty, and relative price dispersion: Evidence from bivariate GARCH-M models," *Journal of Monetary Economics*, 38(2), 391–405.

Grier, K. B., and M. J. Perry (1998): "On inflation and inflation uncertainty in the G7 countries," *Journal of International Money and Finance*, 17(4), 671–689.

——— (2000): "The effects of real and nominal uncertainty on inflation and output growth: Some GARCH-M evidence," *Journal of Applied Econometrics*, 15(1), 45–58.

Grimme, C., S. Henzel, and E. Wieland (2014): "Inflation Uncertainty Revisited: A proposal for robust measurement," *Empirical Economics*, 47(4), 1497–1523.

Grimme, C., and T. Siemsen (2014): "Interbank Uncertainty in a DSGE Model," Mimeo, University of Munich.

Güntner, J. H. (2011): "Competition among banks and the pass-through of monetary policy," *Economic Modelling*, 28(4), 1891–1901.

Hafstead, M., and J. Smith (2012): "Financial Shocks, Bank Intermediation, and Monetary Policy in a DSGE Model," Mimeo, New York University.

Hainz, C., and M. Wiegand (2013): "How does Relationship Banking influence Credit Financing? Evidence from the Financial Crisis," Ifo Working Paper No 157.

Hartmann, M., and H. Herwartz (2014): "Did the introduction of the Euro have an impact on inflation uncertainty? - An empirical assessment," *Macroeconomic Dynamics*, 18(6lein), 1313–1325.

Harvey, A., E. Ruiz, and N. Shephard (1994): "Multivariate Stochastic Variance Models," *Review of Economic Studies*, 61(2), 247–64.

Henzel, S., and M. Rengel (2014): "Dimensions of Macroeconomic Uncertainty: A Common Factor Analysis," CESifo Working Paper No. 4991.

Henzel, S. R., and J. Mayr (2013): "The mechanics of VAR forecast pooling - A DSGE model based Monte Carlo study," *North American Journal of Economics and Finance*, 24(1), 1–24.

Hülsewig, O., E. Mayer, and T. Wollmershäuser (2009): "Bank behaviour, incomplete interest rate pass-through, and the cost channel of monetary policy transmission," *Economic Modelling*, 26(6), 1310–1327.

Imbens, G., and J. M. Wooldridge (2007): "What's New in Econometrics?," *Lecture Notes 6, NBER Summer Institute*, pp. 1–27.

Jovanovic, M., and T. Zimmermann (2010): "Stock Market Uncertainty and Monetary Policy Reaction Functions of the Federal Reserve Bank," *B.E. Journal of Macroeconomics*, 10(1), 1–19.

Jurado, K., S. C. Ludvigson, and S. Ng (2015): "Measuring Uncertainty," *American Economic Review*, 105(3), 1177–1216.

Kadiyala, K. R., and S. Karlsson (1997): "Numerical Methods for Estimation and Inference in Bayesian VAR-Models," *Journal of Applied Econometrics*, 12(2), 99–132.

Kilian, L. (1998): "Small-Sample Confidence Intervals For Impulse Response Functions," *The Review of Economics and Statistics*, 80(2), 218–230.

Kim, S., N. Shephard, and S. Chib (1998): "Stochastic volatility: Likelihood inference and comparison with ARCH models," *Review of Economic Studies*, 65(3), 361–393.

Klenow, P., and O. Kryvtsov (2008): "State-Dependent or Time-Dependent Pricing: Does It Matter For Recent U.S. Inflation?," *The Quarterly Journal of Economics*, 123(3), 863–904.

Knotek, E. S., and S. Khan (2011): "How do households respond to uncertainty shocks?," *Federal Reserve Bank of Kansas City Economic Review*, Q II, 63–92.

Kohlhas, A. N. (2011): "US Monetary Policy & Uncertainty: Testing Brainard's Hypothesis," Mimeo.

Lahiri, K., and X. Sheng (2010a): "Learning and heterogeneity in GDP and inflation forecasts," *International Journal of Forecasting*, 26(2), 265–292.

——— (2010b): "Measuring forecast uncertainty by disagreement: The missing link," *Journal of Applied Econometrics*, 25(4), 514–538.

Lahiri, K., C. Teigland, and M. Zaporowski (1988): "Interest rates and the subjective probability distribution of inflation forecasts," *Journal of Money, Credit and Banking*, 20(2), 233–248.

Leduc, S., and Z. Liu (2015): "Uncertainty Shocks are Aggregate Demand Shocks," Federal Reserve Bank of San Francisco Working Paper 2012-10.

Lein, S. M. (2010): "When Do Firms Adjust Prices? Evidence from Micro Panel Data," *Journal of Monetary Economics*, 57(6), 696–715.

Litterman, R. B. (1986): "Forecasting with Bayesian Vector Autoregressions: Five Years of Experience," *Journal of Business and Economic Statistics*, 4(1), 25–38.

Loupias, C., and P. Sevestre (2013): "Costs, Demand, and Producer Price Changes," *Review of Economics and Statistics*, 95(1), 315–327.

Mackowiak, B., and M. Wiederholt (2009): "Optimal Sticky Prices under Rational Inattention," *American Economic Review*, 99(3), 769–803.

——— (forthcoming): "Business Cycle Dynamics under Rational Inattention," *Review of Economic Studies*.

Mankiw, N. G., R. Reis, and J. Wolfers (2003): "Disagreement about inflation expectations," *NBER Macroeconomic Annual*, 18, 209–248.

Narita, F. (2011): "Hidden Actions, Risk-taking and Uncertainty Shocks," Mimeo, University of Minnesota.

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

Peng, A., and L. Yang (2008): "Modelling uncertainty: A recursive VAR bootstrapping approach," *Economics Letters*, 99(3), 478–481.

Petersen, M. A., and R. G. Rajan (1994): "The Benefits of Lending Relationships: Evidence from Small Business Data," *The Journal of Finance*, 49(1), 3–37.

Popescu, A., and F. R. Smets (2010): "Uncertainty, Risk-Taking, and the Business Cycle in Germany," *CESifo Economic Studies*, 56(4), 596–626.

Rich, R. W., and J. S. Butler (1998): "Disagreement as a measure of uncertainty - A comment on Bomberger (1996)," *Journal of Money, Credit and Banking*, 30(3), 411–419.

Rich, R. W., and J. Tracy (2010): "The relationship among expected inflation, disagreement, and uncertainty: Evidence from matched point and density forecasts," *The Review of Economics and Statistics*, 92(1), 200–207.

Rivers, D., and Q. H. Vuong (1988): "Limited information estimators and exogeneity tests for simultaneous probit models," *Journal of Econometrics*, 39(3), 347–366.

Sargent, T. J. (1999): "Comment: Policy Rules for Open Economies," in *Monetary Policy Rules*, ed. by J. B. Taylor, pp. 127–156. NBER and University of Chicago Press, Chicago.

Scharler, J. (2008): "Do bank-based financial systems reduce macroeconomic volatility by smoothing interest rates?," *Journal of Macroeconomics*, 30(3), 1207–1221.

SCHENKELBERG, H. (2014): "The Determinants of Sticky Prices and Sticky Plans: Evidence from German Business Survey Data," *German Economic Review*, 15(3), 353–373.

SHARPE, S. A. (1990): "Asymmetric Information, Bank Lending and Implicit Contracts: A Stylized Model of Customer Relationships," *The Journal of Finance*, 45(4), 1069–1087.

SHEPHARD, N. (2008): "Stochastic Volatility Models," in *The New Palgrave Dictionary of Economics*, ed. by S. N. Durlauf, and L. E. Blume. Palgrave Macmillan, Basingstoke.

SMETS, F., AND R. WOUTERS (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.

STOCK, J. H., AND M. W. WATSON (1999): "Forecasting inflation," *Journal of Monetary Economics*, 44(2), 293–335.

——— (2002): "Macroeconomic forecasting using diffusion indices," *Journal of the American Statistical Association*, 20(2), 147–162.

——— (2007): "Why has U.S. inflation become harder to forecast?," *Journal of Money, Credit and Banking*, 39(1), 3–33.

TOWNSEND, R. M. (1979): "Optimal Contracts and Competitive Markets with Costly State Verification," *Journal of Economic Theory*, 21(2), 265–293.

VASICEK, O. (1976): "A test for normality based on sample entropy," *Journal of the Royal Statistical Society*, Series B, 38(1), 54–59.

VAVRA, J. (2014): "Inflation Dynamics and Time-Varying Volatility: New Evidence and an Ss Interpretation," *The Quarterly Journal of Economics*, 129(1), 215–258.

VON HEIDEKEN, V. Q. (2009): "How Important are Financial Frictions in the United States and the Euro Area?," *Scandinavian Journal of Economics*, 111(3), 567–596.

Walsh, C. E. (2003): *Monetary Theory and Policy*. The MIT Press.

Williamson, S. D. (1987): "Costly Monitoring, Loan Contracts, and Equilibrium Credit Rationing," *The Quarterly Journal of Economics*, 102(1), 135–145.

Wooldridge, J. M. (2002): *Econometric Analysis of Cross Section and Panel Data*. MIT Press, Cambridge M.A.

Zakovic, S., V. Wieland, and B. Rustem (2007): "Stochastic Optimization and Worst-Case Analysis in Monetary Policy Design," *Computational Economics*, 30(4), 329–347.

Zarnowitz, V., and L. A. Lambros (1987): "Consensus and uncertainty in economic predictions," *Journal of Political Economy*, 95(3), 591–621.

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Christian Grimme