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Increasing Business Uncertainty and Credit Conditions in Times of Low and High Uncertainty: Evidence from Firm-Level Survey Data

Abstract

We demonstrate that the impact of increases in uncertainty on bank credit conditions depends on the level of uncertainty. Using firm-level survey data, we document that a surge in business-specific uncertainty is particularly damaging when this uncertainty is low: low levels nearly triple the effect compared to high levels. The result is robust to controlling for recessionary periods. To provide an interpretation, we build and calibrate a stylized model in which bank lending is governed by expectations about the future level of business uncertainty. Increases in uncertainty serve as a signal to update these expectations. The model predicts that expectations are revised more strongly and, thus, lending drops more under low uncertainty.

JEL-Codes: C230, E320, G210.

Keywords: uncertainty, financial frictions, bank lending, survey data.

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1 Introduction

During the last decade, firms have been confronted with large shifts in uncertainty regarding their business environment. Recent work has well documented that uncertainty leads to a contraction of economic activity (for a survey, see, e.g., Bloom, 2014; Castelnuovo, 2019). One strand of this literature emphasizes the role of financial frictions for the propagation of uncertainty shocks.[1] Due to limited liability, heightened uncertainty about a firm's business outlook impairs financing conditions and reduces the supply of bank loans.[2,3] In this study, we analyze the response of firms' bank credit conditions to increases in business uncertainty.

Our contribution is twofold. First, we provide new empirical evidence for state-dependent effects of uncertainty. To our knowledge, we are the first to study the effect using firm-level data. We document that increases in business-specific uncertainty are most detrimental to a firm's credit conditions at low levels of business-specific uncertainty and least harmful at high levels. Low levels of uncertainty appear to double the negative impact of an increase in uncertainty compared to medium levels and nearly triple the effect compared to high levels. Second, we develop a stylized model in which bank loan supply depends on the bank's expectations about the future level of business uncertainty. We use this model to show how an increase in uncertainty may lead to a larger update of expectations and a stronger decline of lending at low levels of uncertainty.

The state-dependent effects of uncertainty are well documented.[4] Specifically, it has been highlighted that the response to an uncertainty increase may depend on the level of uncertainty. While in our analysis the effect of uncertainty also depends on the level of uncertainty, we suggest that this non-linearity operates via the loan supply behavior of banks. Intuitively, bank lending may be non-linear, since, first, granting a loan at all is usually a yes-or-no decision. For instance, when the bank refuses to assume the risk of a particular indivisible investment project, lending conditions of a bank-financed firm may worsen only once and, thus, do not further deteriorate when uncertainty continues to

[1]See Arellano, Bai, and Kehoe (2019); Bloom, Alfaro, and Lin (2019); Christiano, Motto, and Rostagno (2014); Gilchrist, Sim, and Zakrajšek (2014).

[2]See Alessandri and Bottero (2020); Barraza and Civelli (2019); Bordo, Duca, and Koch (2016); Buch, Buchholz, and Tonzer (2015); Raunig, Scharler, and Sindermann (2017); Valencia (2017).

[3]A complementary channel is documented for financial markets. To compensate for the higher default risk, the risk premium on bonds increases (see, e.g., Gilchrist et al., 2014).

[4]Recent papers suggest recessions, periods of economic or financial distress, or the level of uncertainty as potential states. See, Alessandri and Mumtaz (2019); Angelini, Bacchiocchi, Caggiano, and Fanelli (2019); Bijsterbosch and Guérin (2013); Caggiano, Castelnuovo, and Figueres (2017); Caggiano, Castelnuovo, and Groshenny (2014); Caggiano, Castelnuovo, and Nodari (2017); Jackson, Kliesen, and Owyang (2020); Lhuissier and Tripier (2019); Mumtaz and Theodoridis (2018); Nodari (2014); Salzmann (2020).

increase. Second, if a bank grants a loan, it may be costly to constantly readjust price and non-price lending terms, so that credit conditions may experience a staggered adjustment (see, for instance, Hannan and Berger (1991); Klein (1971), for an example of adjustment cost).[5]

Previous empirical work analyzing the (linear) relation between uncertainty and bank lending relies on aggregate uncertainty measures (see the references in footnote 2), while we rely on firm-specific uncertainty. Our approach may provide additional insight, since business uncertainty may differ systematically across borrowers. After all, banks providing a loan base their decision also on borrower-specific developments. To compute our measure of firm-specific uncertainty, we use confidential micro data from the German Ifo Business Cycle Survey, which contains information about individual production expectations as well as realizations. This enables us to construct a long, monthly history of firm-specific forecast errors following the strategy of Bachmann, Elstner, and Sims (2013). We measure uncertainty using the firm-specific rolling window standard deviation of the forecast errors (Bachmann, Born, Elstner, and Grimme, 2019). Note that the measure neither depends on some form of dispersion among firms, nor does it rest on the assumption of a representative firm.

The unique feature of the Ifo survey data is that it allows to match firm-specific uncertainty and information about the same firm's access to bank credit. Specifically, firms are asked to assess the willingness of banks to hand out credit. Since bank loans are still the predominant form of external finance in Germany, firms' overall financial conditions strongly depend on changes in bank credit conditions (see, e.g., Deutsche Bundesbank, 2014; European Central Bank, 2019; Grimme, 2019). Further, the survey question is targeted at the banks' loan supply decision, which helps to circumvent problems related to equilibrium effects usually present in realized market prices or quantities. Moreover, the survey includes a set of firm-level control variables which help us isolate the effect of uncertainty on credit conditions. We believe that using survey data is particularly valuable in our case, as the survey polls actual decision-makers at firms in contrast to, for instance, financial analysts (Bachmann et al., 2013). Unlike firm-level stock market data, our data encompasses firms of all sizes.

We obtain our baseline results using a linear probability model with firm- and time-fixed effects. We document that a unit increase in business uncertainty raises the likelihood to become credit constraint by about three percentage points when the business environment is highly uncertain. Such an increase in uncertainty is observed, for instance, for 10% of all

[5]Note that, in general, bond markets behave differently, since corporate bond yields usually react instantaneously (see, e.g. Gilchrist and Zakrajšek, 2012).

firms during the financial crisis. Under medium uncertainty, a surge in uncertainty raises the probability for a worsening of credit conditions by about 4½ percentage points. When uncertainty is low, the likelihood that credit conditions deteriorate rises by about eight percentage points. Various robustness checks confirm our results.

Several papers provide a theoretical explanation as to why the effects of uncertainty are stronger in times of recessions or financial distress.[6] We complement this literature by providing an argument as to why the effects of uncertainty increases depend on the level of uncertainty. To explain this non-linearity, we propose a highly stylized model, which emphasizes the role of bank credit conditions.

Building on the notion of financial frictions (Christiano et al., 2014; Gilchrist et al., 2014; Townsend, 1979), we assume that loan supply negatively depends on future business uncertainty. A bank thus has to form expectations about the future level of a borrower's business uncertainty, which can be either low, medium, or high. In turn, expected uncertainty is governed by the probabilities attached to these future business uncertainty states. These transition probabilities are time-varying and adjust when an uncertainty shock is observed. We calibrate the transition probabilities as well as the different levels of uncertainty using data from the Ifo survey.

When business uncertainty is initially low, a bank tends to have a strong prior belief that the borrower's business uncertainty remains low. Observing a surprise increase in uncertainty thus delivers a strong signal for the bank that its initial belief is wrong. As a consequence, the bank considerably reduces the probability that the borrower remains in the low uncertainty state. Moreover, most of the probability mass is directly moved to the high uncertainty state, as opposed to medium uncertainty. All in all, the uncertainty increase triggers a substantial adjustment of the bank's expectations and a large reduction in lending. The key to this prediction is a strong prior belief that the borrower remains in the low uncertainty state.

In contrast, when business uncertainty is high, switching from high to low uncertainty is already deemed quite unlikely prior to the observed increase in uncertainty. Since increasing uncertainty only confirms the prior belief, a bank makes only small adjustments to the transition probabilities and the reduction in lending is small as well.

The remainder of this paper is structured as follows. Section 2 describes the Ifo data, the construction of the firm-level uncertainty measure, and the measure for credit conditions. In Section 3, we introduce the micro-econometric framework and present the effects of

[6]The reasons put forward for this kind of non-linear behavior are time variations in the risk aversion of households, in the degree of irreversibility of investment, and in the degree of financial frictions. See, Caggiano, Castelnuovo, and Pellegrino (2017); Dibiasi (2019); Lhuissier and Tripier (2019).

changes in business uncertainty on credit conditions conditional on the uncertainty level. Furthermore, we provide several robustness checks. Section 4 presents a stylized model to provide an interpretation of the empirical results. The last section concludes.

2 Measuring Uncertainty And Credit Conditions

2.1 Measuring Uncertainty

We derive our measure of economic uncertainty using data from the German Ifo Business Cycle Survey (henceforth Ifo), which is a monthly survey among business entities. From the survey, the Ifo Institute derives the Ifo Business Climate Index, which is a much-followed leading indicator for economic activity in Germany. The Ifo data covers a long time span and contains a high number of participants. We use firm-level survey data from the manufacturing sector starting in 2003 (IBS-IND, 2015). At the beginning of our sample, the average number of respondents is about 2,400; at the end the number declines to 1,800. Firms voluntarily participate in the survey, with only 8% of all firms being one-time participants. On average, firms participate 61 times.

The Ifo data covers all types of firm sizes and sectors (see Table A.1 in Appendix A). About 13% of firms in our sample have less than 20 employees, roughly 36% have more than 20 but less than 100 employees, 43% employed between 100 and 1000 people, and 8% have a workforce of more than 1000. Moreover, the Ifo data covers all relevant sectors of the German manufacturing industry.

To estimate firm-specific uncertainty, we use the following two qualitative questions:[7]

Production ($prod_{i,t}$): Our domestic production activity with respect to product XY has 'increased', 'roughly stayed the same', or 'decreased'.

Production Expectation ($prod^e_{i,t}$): Expectations for the next 3 months: Our domestic production activity with respect to product XY will probably 'increase', 'remain virtually the same', or 'decrease'.

Firms respond to the survey between the beginning and the middle of the month. Therefore, $prod_{i,t}$ is the change in production reported in t about the preceding month,

[7] The questions of the Ifo survey for manufacturing have been translated into English. Firms are explicitly asked to ignore differences in the length of months or seasonal fluctuations. The survey is conducted at the product level, so firms operating in different product groups are asked to fill out different questionnaires. However, only 0.7% of the responses are multiple products (Link, 2020). Therefore, we use the terms 'firm' and 'product' interchangeably.

for instance in the December-survey, firms report the change in production from October to November. Expectations are formed about month t, $t+1$, and $t+2$, for example in the December-survey, firms report expectations for the months December, January, and February.

Firm-specific uncertainty can be derived using individual forecast errors. Following Bachmann et al. (2013), we calculate the firm-specific forecast error $fe_{i,t}$ by comparing the expectation $prod^e_{i,t-3}$ to the realizations in the subsequent three months: $\overline{prod}_{i,t} = prod_{i,t-2} + prod_{i,t-1} + prod_{i,t}$. Since the Ifo survey provides qualitative data, we code a production increase as 1, a decrease as -1, and unchanged production as 0. Therefore, $\overline{prod}_{i,t}$ is in the range $[-3, 3]$. Likewise, $prod^e_{i,t}$ can assume values of 1 (increase), 0 (unchanged), and -1 (decrease). The forecast error is given by the difference between $\overline{prod}_{i,t}$ and $prod^e_{i,t-3}$. The expectation error, $fe_{i,t}$, falls within a range of -4 and 4; for instance, -4 indicates a large negative forecast error: the firm expects production to increase, but production in fact declines in all three months. Table 1 summarizes the possible outcomes of $fe_{i,t}$.

Expectation $prod^e_{i,t-3}$	**Realization** $\overline{prod}_{i,t}$	**Forecast Error** $fe_{i,t}$
Increase	> 0	0
Increase	≤ 0	$\overline{prod}_{i,t} - 1$
Unchanged	> 0	$\overline{prod}_{i,t}$
Unchanged	$= 0$	0
Unchanged	< 0	$\overline{prod}_{i,t}$
Decrease	< 0	0
Decrease	≥ 0	$\overline{prod}_{i,t} + 1$

Table 1: Firm-Specific Forecast Errors. $prod^e_{i,t-3}$ refers to production expectations in the Ifo survey. Realized change in production $\overline{prod}_{i,t}$ is the sum of $prod_{i,t}$, $prod_{i,t-1}$, and $prod_{i,t-2}$, based on the Ifo survey. The index t denotes the time of the survey.

Similar to Comin and Mulani (2006), Davis, Haltiwanger, Jarmin, and Miranda (2006), and Bachmann et al. (2019), among others, we measure firm-level uncertainty using the twelve month rolling window standard deviation of firm i's forecast errors as

$$\sigma_{i,t} = \sqrt{\frac{1}{12}\sum_{k=0}^{11}\left(fe_{i,t+3-k} - \overline{fe}_{i,t+3}\right)^2},$$

where $\overline{fe}_{i,t+3} = \frac{1}{12}\sum_{l=0}^{11} fe_{i,t+3-l}$ is the rolling mean of the forecast error based on a window size of twelve months. Note that $\sigma_{i,t}$ measures uncertainty at the time when expectations are formed. Forming believes about the standard deviation of future errors, firms use production expectations up to period t and production realizations up to period $t+3$. We therefore assume that the current forecast error (which is not observed in real time) and past forecast errors are representative of the uncertainty perceived at time t.[8] Note that this is closely related to the concept of a stochastic volatility model, which provides an estimate of the time varying (expected) forecast error variance based on past experience and the assumption that volatility is persistent.

The uncertainty measure is advantageous along several dimensions. Unlike cross-sectional forecast dispersion measures, which assume a close relationship between disagreement among forecasters and individual uncertainty, our measure, σ_i, is directly related to the variability of the expected forecast error of an individual firm. Moreover, σ_i is robust to first-moment shocks to production, since a bias in the forecast, for instance due to consistent over-prediction or 'optimism', will not affect the standard deviation.

We define a low, a medium and a high uncertainty state. The respective states are defined individually for each firm. Therefore, the perception of uncertainty is based on the firm's individual experience, since firms operating in a more volatile business environment would perceive a different 'normal' than firms who have experienced a steady development in the past. We assume that the uncertainty states are normally distributed within a firm.[9] This assumption implies that the medium uncertainty state contains 68% of the observations, i.e. this state comprises all observations which roughly lie within one standard deviation from the mean. The low (high) regime contains 16% of the lowest (highest) observations.[10]

Table 2 shows that, overall, $\sigma_{i,t}$ has a mean of 0.866 and a standard deviation of 0.372. The standard deviation of $\sigma_{i,t}$ is roughly similar across uncertainty states. We measure the persistence of $\sigma_{i,t}$ using transition probabilities, as presented in Table 3. If a firm faces a low level of uncertainty, there is a 56% likelihood of staying at that level three months later, while the likelihood of moving up to a medium state is 41%. In contrast, starting from a medium level and remaining there has a probability of 74%, while the probability

[8] We thus assume a certain degree of rationality of the firm with respect to the current (expected) forecast error. However, the remaining past forecast errors are readily observable by the firm. In Section 4, we use lagged uncertainty in the regressions, which is observable in real time.

[9] This is a reasonable assumption since uncertainty is not skewed for 85% of the firms, and for 80% of the firms, uncertainty has zero excess kurtosis.

[10] To guarantee that we have enough observations per firm, we drop all firms with less than 10 observations for uncertainty, which amounts to dropping 16.6% of all firms.

of switching to a low or high level is similar (13%). If the firm is highly uncertain, the likelihood of staying highly uncertain is 54%; moving to a medium or low level is 43% and 3%, respectively.

	Obs	Mean	Std	Min	Max
total	130,671	0.866	0.372	0	2.629
low	26,511	0.464	0.261	0	1.605
medium	79,809	0.877	0.269	0.373	2.230
high	24,351	1.267	0.312	0.373	2.629

Table 2: Descriptive Statistics For $\sigma_{i,t}$.

		in t		
		low	medium	high
	low	0.564	0.410	0.027
in t-3	medium	0.133	0.742	0.125
	high	0.030	0.429	0.541

Table 3: Transition Probabilities For Uncertainty States Probabilities of being in the 'low', 'medium' or 'high' uncertainty state conditional on being in either one of the uncertainty states three months earlier.

2.2 Measuring Credit Conditions

In addition to firm-level production expectations and realizations, from which we derive firm-level uncertainty, the Ifo survey also provides the current credit conditions of these firms. Specifically, firms are asked:

Credit Conditions ($C_{i,t}$): How do you assess the current willingness of banks to provide loans? The possible answers are: 'restrictive', 'normal' or 'accommodating'?

The question is posed between June 2003 and December 2015. It is collected at a monthly frequency since November 2008, and bi-annually prior to that.[11] As opposed to credit

[11] Balleer, Hristov, and Menno (2017) use this question to shed light on the interaction between financial frictions and the frequency of price adjustment at the firm-level. Strasser (2013) applies the question to study whether the exchange rate pass through to prices is stronger for financially constrained firms than for unconstrained firms.Fidrmuc and Hainz (2013) show that differences in bank regulation between Austria and Germany influence the banks' willingness to grant loans.

volume measures, which reflect equilibrium outcomes, our measure of credit conditions, $C_{i,t}$, is targeted at supply side factors in the loan market. Given the wording of the question, one could be concerned that a firm's response to this question is about the general assessment of credit conditions. However, Fidrmuc, Hainz, and Hoelzl (2017) show that the firm's perception about credit conditions are evaluated relative to the firm's own individual credit experience. They also demonstrate that a deterioration of credit conditions seems to be reported if either a loan is rejected or because credit conditions are worse than expected by the firm. In addition, Huber (2018) documents that identified changes to a firm's bank loan supply are a strong predictor for the answer to this question.

We might be concerned that a too low variation of credit conditions within the low or the high uncertainty state precludes identifying any effect in these states. However, this appears not to be a problem. Table 4 shows the transition probabilities attached to different credit conditions for each uncertainty state. For instance, the probability to switch from 'restrictive' to 'normal' lies between 16% and 18% irrespective of the uncertainty state. Furthermore, a tightening of credit conditions can be observed among highly uncertain firms. Thus, there appears to be substantial variation of lending conditions, even among firms in a high or low uncertainty state.

		Low Uncertainty in $t-3$			Medium Uncertainty in $t-3$			High Uncertainty in $t-3$		
			in t			in t			in t	
		restr	normal	accomm	restr	normal	accomm	restr	normal	accomm
	restr	0.831	0.161	0.008	0.813	0.181	0.006	0.814	0.179	0.006
in $t-3$	normal	0.052	0.907	0.041	0.061	0.898	0.041	0.068	0.886	0.046
	accomm	0.011	0.203	0.786	0.013	0.227	0.760	0.014	0.205	0.781

Table 4: Transition Probabilities For $C_{i,t}$ For Different Uncertainty States. Probability to answer 'restrictive', 'normal' or 'accommodating' to the question on credit conditions, $C_{i,t}$, conditional on being in one of the credit categories three months earlier, and conditional on being in each of the uncertainty states three months earlier.

3 Empirical Analysis

3.1 The Empirical Model

We use the following model to estimate the effects of an increase in uncertainty on credit conditions at a monthly frequency:

$$C_{i,t} = A_i + \left(\alpha_0 + \alpha_1\, d_{t-3}^{low} + \alpha_2\, d_{t-3}^{high}\right) \sigma_{i,t-3} + BX_{i,t} + \varepsilon_{i,t}, \tag{1}$$

where $C_{i,t}$ is firm i's perception of bank credit conditions, which is equal to 1 if a firm perceives the lending policy as restrictive, 0 if it is perceived as normal, and -1 if it is accommodating. The variable $\sigma_{i,t-3}$ denotes the uncertainty of firm i in period $t-3$. We lag firm's uncertainty by three months to circumvent the issue of endogeneity.[12] Since $\sigma_{i,t}$ includes production realizations of months t, $t+1$, and $t+2$ (surveyed in $t+1$, $t+2$, and $t+3$), among others, we lag the variable by three months, so that $\sigma_{i,t-3}$ contains realizations up to month $t-1$. The constant A_i captures firm-specific fixed effects and $\varepsilon_{i,t}$ represents the error term.

We let the impact of uncertainty vary across the three discrete uncertainty states. The dummy variable $d^{low}_{i,t-3}$ equals 1 if the level of uncertainty of firm i in period $t-3$ is defined as *low*, and 0 otherwise, and we set $d^{high}_{i,t-3}$ equal to 1 for a firm which experiences *high* uncertainty.[13] Choosing these dummy variables ensures a sufficient number of observations as well as a substantial variation of credit conditions within each uncertainty state (compare Table 4 in Section 2.2). Equation (1) nests the linear model; if $\alpha_1 = \alpha_2 = 0$, we would reject the state-dependence of the impact of uncertainty.

The vector $X_{i,t}$ includes additional control variables. One of the advantages of the Ifo data is that it includes several firm-level variables, which allow us to control for first-moment effects. The variable *Business Situation* is indicative of a firm's current business situation. The forward-looking variables *Business Expectation* and *Expected Employees* are included to control for optimism or pessimism. All the variables have three possible response categories. Responses indicating a 'good' business situation, or improving business or employment expectations are coded as 1, a 'satisfactory' situation or unchanged expectations as 0, and an 'unsatisfactory' situation or deteriorating expectations as -1, respectively. Appendix B provides a detailed description of the variables. We also add time-fixed effects to control for common trends in credit conditions which might also be related to uncertainty, such as monetary policy changes.

3.2 Baseline Results

We estimate model (1) using observations from June 2003 to December 2015. We obtain our baseline results using a linear fixed effects model. One advantage of this model is that the coefficients can be readily interpreted as marginal effects. Further, it controls

[12] Due to the bi-annual nature of the data before November 2008, we use for the earlier period the value six months before.

[13] Note that using dummy variables to model the non-linearity – instead of $\sigma_{i,t-3}$ itself – introduces flexibility, since we do not restrict the influence of the uncertainty level on the coefficient. Particularly, the coefficient may not be proportionate to the level of uncertainty.

for unobservable individual characteristics, which can influence the impact of uncertainty on lending conditions. For instance lenders might be more reluctant to provide a loan to small firms with a highly uncertain business model. Alternatively, if we re-define the three-scale dependent variable to a binary variable, the model can be estimated using a fixed effects logit estimator. While non-linear estimators may explicitly account for the categorical nature of our dependent variable, only the sign of the estimated coefficients can be interpreted, since the marginal effect depends on the unobserved fixed effect (see, e.g., Cameron and Trivedi, 2005). Nevertheless, we present coefficient results for non-linear estimators in robustness Section 3.3.

Table 5 presents the estimation results for the baseline panel fixed effects model. The standard errors are clustered at the firm level. The model in column (1) includes firm-level uncertainty and the interaction of uncertainty with d_{t-3}^{low} ('Uncertainty low') and d_{t-3}^{high} ('Uncertainty high') in addition to a constant and a set of time-fixed effect dummies. The model in column (2) contains, in addition, the set of firm-specific variables described in Section 3.1.

Concerning the control variables in column (2), both, current conditions as well as future conditions have a significant impact on credit conditions. Firms whose current business situation improves have a 5.8 percentage points lower likelihood that lending conditions tighten. The likelihood for a tightening of credit conditions declines by 1.3 percentage points for firms with improving business expectations, and improved employment expectations reduce the likelihood by 2.8 percentage points.

Table 5 demonstrates that a unit increase in uncertainty raises the probability that credit conditions are assessed as more restrictive by 4.8 percentage points when firms experience a medium level of uncertainty. When we add firm-specific control variables, the coefficient in column (2) reduces only slightly to 4.2, which suggests that the uncertainty measure is indeed largely unrelated to first-moment shocks.

Moreover, we observe that the impact in both the low and the high uncertainty state differs significantly from the medium uncertainty state. According to column (1), the impact of uncertainty is amplified by 3.4 percentage points when firms experience a low uncertainty state. Therefore, an increase in uncertainty from a low level raises the probability that a firm perceives tighter credit conditions by 8.2 percentage points, or by 7.6 percentage points when we consider column (2). In contrast, the impact of uncertainty appears to be dampened by 1.5 to 1.6 percentage points at a high level of uncertainty when compared to the medium uncertainty state. Under high uncertainty, a unit increase in uncertainty thus raises the probability that lending conditions tighten only by 2.7 to 3.2 percentage points. Overall, when uncertainty is low, the effects of an increase in uncer-

Dependent Variable: Credit Conditions $C_{i,t}$		
	(1)	(2)
Uncertainty α_0	0.048***	0.042***
	(0.015)	(0.015)
Uncertainty low α_1	0.034***	0.034***
	(0.011)	(0.011)
Uncertainty high α_2	-0.016**	-0.015**
	(0.006)	(0.006)
Business Situation		-0.058***
		(0.006)
Business Expectation		-0.013***
		(0.005)
Expected Employees		-0.028***
		(0.007)
No. of obs.	66,014	65,729
R-squared	0.587	0.590

* p < 0.10, ** p < 0.05, *** p < 0.01.

Table 5: Baseline Results. The table reports coefficients; clustered (by firm) standard errors in parentheses; estimated using a linear panel fixed effects model. Included in all models but not shown in the table are time-fixed effects for each month and a constant. Model (2) includes, in addition, all firm-specific variables described in Section 3.1. Uncertainty regimes *low* and *high* cover the 16% lowest and highest observations at the firm level for uncertainty. The dependent variable is categorical and equals -1 if a firm perceives lending terms as accommodative, 0 for normal, and +1 for restrictive perceptions.

tainty are 1.7 to 1.8 times stronger compared to the medium uncertainty state and 2.6 to 2.8 times stronger compared to the high uncertainty state.

To put these estimates into perspective, note that firm-level uncertainty has a standard deviation of 0.372 (compare Table 2). Therefore, an increase of uncertainty by one unit translates into an increase of 2.7 standard deviations. Further, we may zoom in on the Great Financial Crisis (January 2008 to April 2009), when business uncertainty has increased for many firms. During this period, 1% of the firms have experienced an increase in uncertainty of more than 1.3 units, 10% of the firms have seen a one unit increase or greater, and 25% of the firms have seen uncertainty rise by more than 0.7 units.

Overall, our results suggest that an increase in uncertainty deteriorates a firm's credit conditions and that this effect is state-dependent. Lending terms react the most at low levels of uncertainty. In contrast, increases in uncertainty are least harmful at high levels of uncertainty.

3.3 Robustness Of The Results

To further substantiate our results, we conduct several supplementary analyses. First, we study whether our results are driven by the development recessionary and non-recessionary times. Second, we use non-linear panel estimators. Third, further checks are related to potential measurement issues in the construction of the uncertainty variable, such as the definition of the thresholds for either low and high uncertainty, the history of forecast errors used to compute the error's standard deviation, and calculating the forecast error's standard deviation based on past and future forecast errors.

Recessionary Periods Several papers show that increases in uncertainty are particularly harmful during recessions (see, for instance, Caggiano et al., 2017, 2014, 2017; Nodari, 2014). Since recessions are typically accompanied by rising uncertainty, we analyze whether our results can be reconciled with earlier findings. To control for different recession phases, we interact uncertainty with a recession dummy, such that the impact of uncertainty on credit conditions may vary with the uncertainty state *and* the business cycle. Recessions are dated by the German Council of Economic Experts, which reports a recession in the year 2003 and during the years 2008/09.

Table 6 shows that low uncertainty amplifies the effect in both, recessionary and non-recessionary times. Recessions appear to reinforce the non-linearity, particularly when uncertainty is at low or medium levels. The likelihood that credit conditions tighten in the low uncertainty state is about 8 to 9 percentage points higher when compared to non-recessionary times. In times of medium uncertainty, the effect is between 6 to 7 percentage points higher during recessions. While these results confirm earlier outcomes, they also corroborate that the effects of changes in uncertainty depend on the level of uncertainty irrespective of whether there is a recession or not.

Logit Estimation Despite the linear probability model having some merits as discussed in Section 3.2, probabilities are often modeled using non-linear estimators to avoid in-sample predicted probabilities being either less than zero or greater than one. Although we do not encounter this problem, we check whether a conditional fixed effects logit estimator yields different results. Like the linear estimator, it controls for unobserved individual heterogeneity, but no estimated values of the individual fixed effects are provided. There-

Dependent Variable: Credit Conditions $C_{i,t}$		
	(1)	(2)
Uncertainty α_0	0.042***	0.037**
	(0.016)	(0.015)
Uncertainty low α_1	0.027**	0.027**
	(0.012)	(0.011)
Uncertainty high α_2	-0.017**	-0.015**
	(0.007)	(0.007)
Uncertainty × Recession	0.069**	0.058*
	(0.034)	(0.034)
Uncertainty low × Recession	0.083**	0.088**
	(0.042)	(0.042)
Uncertainty high × Recession	0.009	0.007
	(0.023)	(0.023)
Control Variables	no	yes
No. of obs.	66,014	65,729
R-squared	0.587	0.590

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: Robustness: Uncertainty Interacted With Recession Dummy. The table reports coefficients, clustered (by firm) standard errors in parentheses and estimated using a linear panel fixed effects model. Included in all models but not shown in the table are time-fixed effects for each month and a constant. Model (2) includes, in addition, all firm-specific variables described in Section 3.1. Uncertainty regimes *low* and *high* cover the 16% lowest and highest observations at the firm level for uncertainty. The dependent variable is categorical and equals -1 if credit conditions are accommodative, 0 if credit conditions are normal, and +1 if credit conditions are restrictive. Recessions are dated by the German Council of Economic Experts: 2003m1–2003m6 and 2008m1–2009m4.

fore, it is not possible to compute marginal effects and we can interpret only the signs of the coefficients. Further, it can only be applied to binary response variables. We thus define two binary variables: 'Restrictive' ('Accommodative') is equal to 1 if a firm perceives lending terms as restrictive (accommodative) and 0 for normal perceptions. When we use these re-defined dependent variables, we can also assess whether the effect of uncertainty differs between firms moving from normal to restrictive or to accommodative credit conditions.

For comparison, in panel (a) Table 7 shows the results from the linear estimator using binary dependent variables. Considering columns (1) and (2), it appears that rising uncertainty is associated with more restrictive credit conditions at medium uncertainty levels, and lending terms become even more restrictive when uncertainty is low, while we observe a smaller effect when uncertainty is high. However, columns (3) and (4) reveal, that at medium levels of uncertainty, there is little evidence of lending becoming less accommodative. Yet, the impact of uncertainty seems to be amplified when uncertainty is low, while there is almost no reaction towards a less accommodating stance when firms are highly uncertain. Such a finding suggests that most of lending conditions' response to heightened uncertainty stems from more restrictive lending.

In panel (b) we document coefficient values from the non-linear estimator, which qualitatively replicate the findings from the linear estimator. The results from the logit estimator reinforce the notion that in response to rising uncertainty, credit conditions particularly deteriorate when uncertainty is low. Appendix C provides further results from a fixed effects ordered logit model. These estimations also corroborate our baseline results.

Dependent Variable: Credit Conditions $C_{i,t}$	Restrictive		Accommodative		Restrictive		Accommodative	
	(a) FE OLS				(b) FE Logit			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Uncertainty α_0	0.038***	0.034***	-0.010	-0.008	0.448***	0.398***	-0.241**	-0.226**
	(0.012)	(0.012)	(0.009)	(0.008)	(0.075)	(0.075)	(0.099)	(0.100)
Uncertainty low α_1	0.017**	0.017**	-0.017**	-0.017**	0.241***	0.238***	-0.264***	-0.258***
	(0.008)	(0.008)	(0.007)	(0.007)	(0.078)	(0.079)	(0.098)	(0.099)
Uncertainty high α_2	-0.010**	-0.009*	0.006*	0.006	-0.095**	-0.079**	0.163***	0.161***
	(0.005)	(0.005)	(0.003)	(0.003)	(0.038)	(0.038)	(0.050)	(0.051)
Control Variables	no	yes	no	yes	no	yes	no	yes
No. of obs.	66,014	65,729	66,014	65,729	47,188	46,920	32,031	31,872
R-squared	0.545	0.547	0.531	0.533				
Pseudo R-Squared					0.140	0.150	0.079	0.095

* p < 0.10, ** p < 0.05, *** p < 0.01.

Table 7: Robustness: Binary Dependent Variables. The table reports coefficients, clustered (by firm) standard errors in parentheses. Models (1) to (4) are estimated using linear panel fixed effects estimator, models (5) to (8) are estimated using the conditional fixed effects logit estimator. Included in all models but not shown in the table are time-fixed effects for each month. In addition, models (2), (4), (6), and (8) include all firm-specific variables described in Section 3.1. Uncertainty states 'low' and 'high' cover the 16% lowest and highest observations at the firm level. The dependent variable 'Restrictive' ('Accommodative') equals 1 if credit conditions are restrictive (accommodative) and 0 if credit conditions are normal or accommodative (restrictive).

Thresholds For Uncertainty States In the baseline specification, the medium uncertainty state contains 68% of the uncertainty observations of a firm and the low and high states are characterized by the 16% lowest or highest observations. As a further robustness check, we increase the number of observations belonging to the low or high state by successively raising the respective thresholds to 20%. Since the firm-specific uncertainty measure is quasi-continuous, using less observations in the high and low uncertainty state would markedly reduce the variation of uncertainty within a particular state. This would hamper the identification of the effect. While more observations in either the high or low uncertainty state could help to better identify the effect, the distinction between different states is less pronounced and effects might wash out. The estimates shown in Table 8 are, however, very similar to the baseline estimates.

Dependent Variable: Credit Conditions $C_{i,t}$								
Uncertainty Threshold	17%		18%		19%		20%	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Uncertainty α_0	0.047***	0.043***	0.046***	0.041***	0.052***	0.047***	0.052***	0.047***
	(0.015)	(0.015)	(0.016)	(0.015)	(0.015)	(0.015)	(0.016)	(0.016)
Uncertainty low α_1	0.032***	0.033***	0.029***	0.030***	0.033***	0.034***	0.033***	0.033***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.010)	(0.010)
Uncertainty high α_2	-0.015**	-0.014**	-0.014**	-0.013**	-0.016**	-0.015**	-0.015**	-0.014**
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(0.006)
Control Variables	no	yes	no	yes	no	yes	no	yes
No. of obs.	66,465	66,180	67,145	66,856	68,097	67,801	68,832	68,530
R-squared	0.586	0.590	0.586	0.590	0.585	0.589	0.582	0.587

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 8: Robustness: Varying Thresholds For Uncertainty States. The table reports coefficients, clustered (by firm) standard errors in parentheses and estimated using a linear panel fixed effects model. Included in all models but not shown in the table are time-fixed effects for each month and a constant. Model (2) includes, in addition, all firm-specific variables described in Section 3.1. Uncertainty regimes *low* and *high* cover the 17% / 18% / 19% or 20% lowest and highest observations at the firm level for uncertainty. The dependent variable is categorical and equals -1 if credit conditions are accommodative, 0 if credit conditions are normal, and +1 if credit conditions are restrictive.

Window Size Of Uncertainty Measure Thus far, the uncertainty measure is based on a window of 12 forecast errors. We change the window size and instead use 10, 11, 13, and 14 monthly forecast errors. For each of the alternative measures, we re-compute the thresholds for the three uncertainty states whereby 68% of a firm's observations are in the medium state, and the low (high) state contains 16% of the lowest (highest) observations. Note that, due to the qualitative nature of the forecast errors, the uncertainty measure is quasi-continuous and the number of possible realizations of firm-specific uncertainty shrinks when we reduce the window size. As a consequence, variation within a particular uncertainty state decreases.

The results are presented in Table 9. The signs of the coefficients are identical to the baseline specification, and the coefficients are also significant. For a window size of 13 and 14 months the coefficients are comparable to the baseline, while coefficients are smaller for window size 10 and 11. Overall, the non-linear effect of uncertainty does not depend on a particular window size. Computing the uncertainty measure using a window size of less than about 11 months reduces the variation within each uncertainty state such that it is apparently difficult to identify the effect.

Dependent Variable: Credit Conditions $C_{i,t}$								
Window Size	10m	10m	11m	11m	13m	13m	14m	14m
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Uncertainty α_0	0.029**	0.025*	0.036***	0.032**	0.045***	0.040**	0.047***	0.041**
	(0.013)	(0.013)	(0.014)	(0.014)	(0.016)	(0.015)	(0.016)	(0.016)
Uncertainty low α_1	0.021*	0.023*	0.026**	0.027**	0.034***	0.034***	0.028**	0.027**
	(0.012)	(0.012)	(0.012)	(0.012)	(0.011)	(0.011)	(0.011)	(0.011)
Uncertainty high α_2	-0.011*	-0.010*	-0.014**	-0.013**	-0.014**	-0.012*	-0.015**	-0.013*
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Control Variables	no	yes	no	yes	no	yes	no	yes
No. of obs.	65,137	64,858	65,893	65,607	65,902	65,619	65,382	65,094
R-squared	0.587	0.591	0.585	0.589	0.586	0.590	0.585	0.589

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 9: Robustness: Window Size Of Uncertainty $\sigma_{i,t}$. The table reports coefficients, clustered (by firm) standard errors in parentheses and estimated using a linear panel fixed effects model. Included in all models but not shown in the table are time-fixed effects for each month and a constant. Model (2) includes, in addition, all firm-specific variables described in Section 3.1. Uncertainty is measured by an asymmetric 10- / 11- / 13- or 14-month rolling window standard deviation of a firm's forecast errors, lagged by three months. Uncertainty regimes *low* and *high* cover the 16% lowest and highest observations at the firm level for uncertainty. The dependent variable is categorical and equals -1 if credit conditions are accommodative, 0 if credit conditions are normal, and +1 if credit conditions are restrictive.

Symmetric Window For Uncertainty Measure Our baseline uncertainty measure is derived from past and present forecast errors, that is we use an asymmetric window to construct the rolling standard deviation of forecast errors. The proceeding is thus similar to an econometrician who makes an assessment using a stochastic volatility model, which estimates expected forecast error variance based on past forecast errors. However, if we assume rational expectations on the part of decision makers, our uncertainty measure could also contain forecast errors from subsequent months that are only observed ex-post. As a robustness check we, thus, construct uncertainty using a symmetric window, which includes past and expected future forecast errors:

$$\sigma_{i,t}^{sym} = \sqrt{\frac{1}{13} \sum_{k} \left(fe_{i,t+3+k} - \overline{fe}_{i,t+3}^{sym} \right)^2},$$

where $\overline{fe}_{i,t+3}^{sym}$ is the average of $fe_{i,t+3+k}$ for $k \in \{-6, -5, \ldots, -1, 0, 1, \ldots, 5, 6\}$. We recompute the firm-specific thresholds for the three uncertainty states. As before, we lag uncertainty by three months.

Table 10 shows that the non-linear effects remain, and the effects are even stronger in terms of size and significance of the coefficients. In particular, coefficients for the medium and the high state become larger. At a medium uncertainty level, an increase in uncertainty is associated with an increase in the likelihood of more restrictive lending conditions by 5 to 6 percentage points; at a low level by 9 to 10 percentage points and at a high level by 3 to 4 percentage points.

Dependent Variable: Credit Conditions $C_{i,t}$		
	(1)	(2)
Uncertainty α_0	0.060***	0.052***
	(0.017)	(0.017)
Uncertainty low α_1	0.036***	0.037***
	(0.012)	(0.012)
Uncertainty high α_2	-0.020***	-0.020***
	(0.006)	(0.006)
Control Variables	no	yes
No. of obs.	61,208	60,958
R-squared	0.590	0.594

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 10: Robustness: Symmetric Window For Uncertainty. The table reports coefficients, clustered (by firm) standard errors in parentheses and estimated using a linear panel fixed effects model. Included in all models but not shown in the table are time-fixed effects for each month and a constant. In addition, model (2) includes all firm-specific variables described in Section 3.1. Uncertainty is measured using a symmetric 13-month rolling window standard deviation of a firm's forecast errors, lagged by three months. Uncertainty regimes *low* and *high* cover the 16% lowest and highest observations at the firm level for uncertainty. The dependent variable is categorical and equals -1 if credit conditions are accommodative, 0 if credit conditions are normal, and +1 if credit conditions are restrictive.

4 A Stylized Model For Loan Supply

4.1 Setup

To provide an interpretation of our empirical results, we develop a stylized model for loan supply. Motivated by the financial frictions channel, credit conditions negatively depend on uncertainty, since higher business uncertainty is associated with a higher default probability of the firm.[14] We further assume that a bank reacts through a reduction in lending, while bank loan rate spreads and non-price lending terms remain unchanged (see, for instance, Grimme, 2019, for a discussion).

Against this background, we assume that the loan volume provided by a bank, C, is inversely related to the level of business uncertainty in period 1, which can be either low, medium, or high: $\sigma_1 \in \{\sigma_L, \sigma_M, \sigma_H\}$. There are two periods. In the beginning of period 1 a risk-neutral bank decides on the amount of credit. The loan is repaid at the end of period 2 if the borrower has not defaulted before. Since the loan is provided for two periods, the bank has to take into account that the borrower may move to a different uncertainty state in period 2. Loan supply by a representative bank is linked to uncertainty via a Cobb-Douglas function:

$$\log C = \alpha \log \frac{1}{\sigma_1} + (1-\alpha) \log \frac{1}{\sigma_2^e} \ , \tag{2}$$

where σ_2^e is the expected uncertainty state in period 2 and α defines the relative importance of the two periods. Equation (2) can also be interpreted as a loan production function in which uncertainty – or its inverse, i.e. certainty – serves as the input. Since banks continuously screen and monitor their borrowers (see, for instance, Boot, 2000; Fiore and Uhlig, 2011), we further assume that the bank can observe the firm's uncertainty.

In the beginning of period 1, a sudden increase in uncertainty, $\hat{\sigma}$, occurs. The bank, thus, needs to form expectations about the second period, which, in general, will depend on the likelihood of each uncertainty regime, since $\sigma_2^e = E\left[\sigma_2 | \sigma_1 = \sigma_i\right] = \rho_{iL}\sigma_L + \rho_{iM}\sigma_M + \rho_{iH}\sigma_H$, where the conditional transition probabilities of moving from uncertainty state i in period 1 to state j in period 2 are denoted by ρ_{ij}. The bank may adjust these transition

[14]Firms finance their investment projects through bank loans. If the return on such an investment is relatively low, the firm cannot repay the loan and defaults. Assuming credit market imperfections in the form of costly state verification (Townsend, 1979), borrower default entails a dead-weight loss, captured by bankruptcy costs. An increase in business uncertainty raises the dispersion of the investment returns and increases the probability of low returns, which implies a higher default rate. Under limited liability, a higher default probability increases the expected costs for banks. This raises lending costs and lowers lending volumes (Christiano et al., 2014; Gilchrist et al., 2014).

probabilities when it observes an uncertainty shock. Table 11 shows how this update is conducted.

Conditional Transition Probabilities ρ_{ij}				
		Uncertainty state j		
		L	M	H
	L	$1-\rho_{LM}-\rho_{LH}$	$\Phi\left[z^*_{ij}+\hat{\sigma}\right]$	$\Phi\left[z^*_{ij}+\hat{\sigma}\right]$
Uncertainty state i	M	$\Phi\left[z^*_{ij}-\hat{\sigma}\right]$	$\Phi\left[z^*_{ij}-\hat{\sigma}\right]$	$1-\rho_{ML}-\rho_{MM}$
	H	$\Phi\left[z^*_{ij}-\hat{\sigma}\right]$	$\Phi\left[z^*_{ij}-\hat{\sigma}\right]$	$1-\rho_{HL}-\rho_{HM}$

Table 11: Conditional Transition Probabilities: This table demonstrates how the sudden change in uncertainty affects the transition probabilities. Initial states i are in rows, and final states j are in columns. Φ denotes the standard lognormal CDF and the parameter z^*_{ij} is chosen such that in the absence of uncertainty shocks: $\rho^*_{ij}=\Phi\left(z^*_{ij}\right)$. ρ_{ij} is the conditional and ρ^*_{ij} is the unconditional transition probability.

The conditional transition probability ρ_{ij} depends on the uncertainty shock in period 1, as well as the currently observed uncertainty state i. We model probabilities using the standard lognormal CDF Φ. The parameter ρ^*_{ij} denotes the unconditional probability of moving from uncertainty state i to state j before the shock has occurred. The parameter z^*_{ij} is determined such that in the absence of uncertainty shocks: $\rho^*_{ij}=\Phi\left(z^*_{ij}\right)$. The bank updates its prior belief in light of an uncertainty shock. A positive shock $\hat{\sigma}$ increases the likelihood of a higher uncertainty state in period 2, while reducing the probability of a lower uncertainty state. The size of this adjustment is directly proportional to the magnitude of the uncertainty shock.[15]

4.2 Model Predictions

The model's parameters are summarized in Table 12. We set the Cobb-Douglas parameter α to 0.5. All other parameters can be calibrated using the data from the Ifo survey. The uncertainty states (σ_L, σ_M, and σ_H) are calibrated to the average values of business uncertainty across all firms in the respective state and correspond to the values previously shown in Table 2. The uncertainty shock $\hat{\sigma}$ equals half the difference between the medium and low uncertainty state, i.e. $\hat{\sigma}=0.205$.[16] The choice of $\hat{\sigma}$ guarantees that the shock is not large enough to initiate an instantaneous switch to a higher uncertainty state. We,

[15]In principle, the adjustment could be based on some optimality criterion using, for instance, filtering techniques. While this may be a fruitful line of research, we believe that modeling an optimal reaction is beyond the scope of this paper.

[16]Half the difference between the medium and the high uncertainty state yields a similar value (0.185).

thus, ensure that, even though banks readily observe the shock, it only affects lending via changed expectations. Second, we need to calibrate the unconditional probabilities ρ^*_{ij}, which correspond to those previously shown in Table 3. Reassuringly, given this calibration, more loans are provided under low uncertainty than under high uncertainty, both before and after an uncertainty shock.

Parameter	Value	Description
σ_L	0.47	Low uncertainty
σ_M	0.88	Medium uncertainty
σ_H	1.25	High uncertainty
$\hat{\sigma}$	0.205	Uncertainty shock
α	0.5	Weight in loan supply
ρ^*_{LL}	0.37	Low uncertainty unchanged
ρ^*_{LM}	0.54	Low to medium uncertainty
ρ^*_{LH}	0.09	Low to high uncertainty
ρ^*_{ML}	0.21	Medium to low uncertainty
ρ^*_{MM}	0.60	Medium uncertainty unchanged
ρ^*_{MH}	0.19	Medium to high uncertainty
ρ^*_{HL}	0.10	High to low uncertainty
ρ^*_{HM}	0.54	High to medium uncertainty
ρ^*_{HH}	0.36	High uncertainty unchanged

Table 12: Calibrated Parameter Values.

In Figure 1 we present the adjustment of the transition probabilities after an uncertainty shock has occurred. Irrespective of the uncertainty state in period 1, the shock leads to a downward revision of the likelihood of remaining in or switching to the low state, ρ_{iL} (left panel). Here, the largest downward revision occurs when the low uncertainty state prevails in period 1, ρ_{LL}. The reason is that firms put a high prior on remaining in the low uncertainty state. A sudden increase in uncertainty is inconsistent with the prior belief that uncertainty will remain low. Therefore, the downward revision of ρ^*_{LL} is relatively strong. In contrast, the likelihood of a switch from high to low uncertainty is comparatively small prior to the shock. Subsequently, the uncertainty shock induces a relatively weak downward revision of ρ^*_{HL}.

Simultaneously, most of the increase in counter-probabilities occurs for ρ_{LH}, while the rise in ρ_{LM} is muted. Moving from low to medium uncertainty was already deemed quite likely before the uncertainty shock. Hence, the conditional likelihood, ρ_{LM}, increases only by a relatively small amount (middle panel). In contrast, a move from low to high uncertainty is considered as very unlikely prior to the shock, ρ^*_{LH}, so that the conditional probability is adjusted upwards much more heavily, ρ_{LH} (right panel).

The change of ρ_{LH} is larger than the absolute change of ρ_{HL}, even though the unconditional probability ρ^*_{LH} is similar in size compared to ρ^*_{HL}. This is crucial for a more pronounced drop in lending at low levels of uncertainty than at high levels. The reason is that ρ_{HL} cannot become smaller than zero. As a consequence, the likelihood of remaining in the high state, ρ_{HH}, can only increase to a certain extent. Therefore, the change of ρ_{HH} is also smaller than the absolute change of ρ_{LL}.

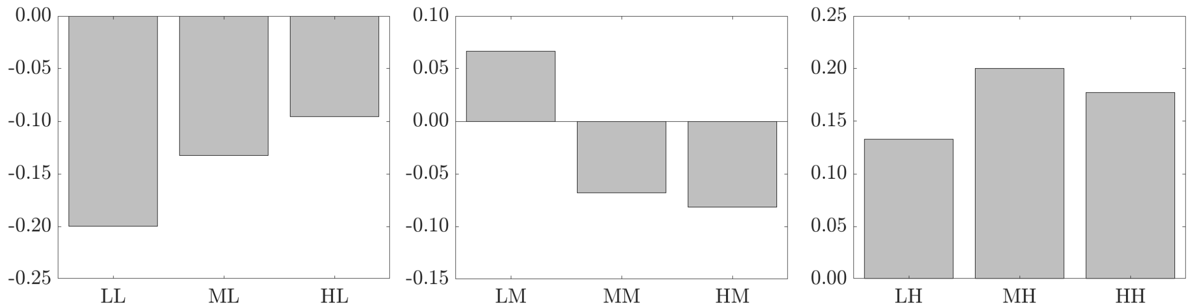

Figure 1: Change In Transition Probabilities. This figure demonstrates the change in transition probabilities for each uncertainty state after a sudden increase in uncertainty. It presents the change in period 2 conditional on each uncertainty regime in period 1 for the low uncertainty state (left), the medium uncertainty state (middle), and the high uncertainty state (right). Changes are given in percentage points. Calculations are based on the parametrization shown in Table 12.

Given the adjustment of the transition probabilities, Figure 2 plots the response of the loan volume to an uncertainty shock in each of the three uncertainty states. Simple changes are depicted in the left panel. Indeed, the reduction in loans is the largest when the level of uncertainty is low. However, a large response under low uncertainty might simply reflect the fact that unconditional loan supply is largest under low uncertainty.

To meet this concern, we depict percentage changes in the right panel of Figure 2, which confirms that the largest effect is indeed obtained under low uncertainty. Overall, banks tend to update their expectations more strongly after an uncertainty shock when firms operate under low uncertainty. Intuitively, when the prior belief is strong that uncertainty will remain low, an uncertainty shock tends to convey a strong signal for the bank to update its expectations. This updating mechanism may, thus, provide an explanation for our empirical findings.

To assess the sensitivity of our model to the calibration, we document the effect of different prior beliefs ρ^*_{iL} on the model's prediction. Specifically, we vary ρ^*_{LL} between

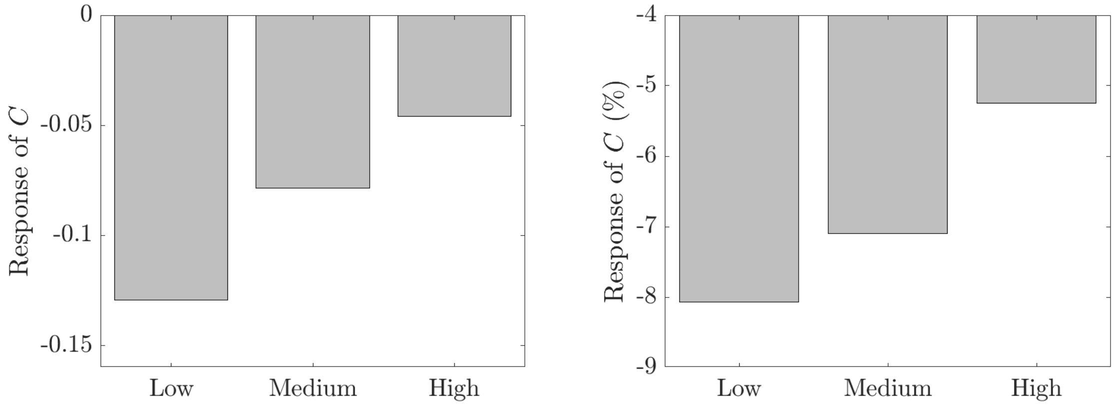

Figure 2: Response Of Loans To Uncertainty Shock. Change in loans in the three uncertainty states after a sudden increase in uncertainty. The left panel shows changes, and the right panel depicts percentage changes based on different levels of uncertainty. Calculations are based on the parametrization shown in Table 12.

0.2 and 0.9 and ρ^*_{HL} between 0.1 and 0.8.[17] The remaining probabilities attached to the medium or high uncertainty state are given as the residual values $\rho^*_{iM} = \rho^*_{iH} = 0.5(1 - \rho^*_{iL})$ for $i \in \{L, H\}$, while the values for the three uncertainty levels are chosen as before (compare Table 12).

To facilitate matters, we only consider the low and the high uncertainty state here. The gray areas in Figure 3 represent parameter combinations in which the percentage drop in lending under low uncertainty is larger than under high uncertainty conditional on the uncertainty shock, i.e. the model's prediction conforms to the empirical evidence. The area in white depicts all constellations leading to a larger drop in lending in the high uncertainty state. The left panel contains calculations for our baseline shock size: $\hat{\sigma} = 0.5\,(\sigma_M - \sigma_L) = 0.205$.

It appears that when ρ^*_{LL} is small, i.e. around 0.2, we observe a larger response under high uncertainty for most values of ρ^*_{HL}. However, when the prior belief to remain in the low uncertainty state becomes larger, i.e. above about 0.4, the largest response is obtained in the low uncertainty state, regardless of the value of ρ^*_{HL}. A small value for ρ^*_{HL}, as found in our baseline calibration, is associated with a larger drop in lending in the low uncertainty state for a wide range of values for ρ^*_{LL}. Reducing the shock size to $\hat{\sigma} = 0.1\,(\sigma_M - \sigma_L) = 0.041$ slightly increases the parameter region for which the model

[17]More extreme combinations are not feasible, since the remaining probabilities may become negative after an uncertainty shock.

conforms to the empirical evidence (right panel). Overall, it appears that a larger response under low uncertainty can be obtained for a wide range of prior beliefs.

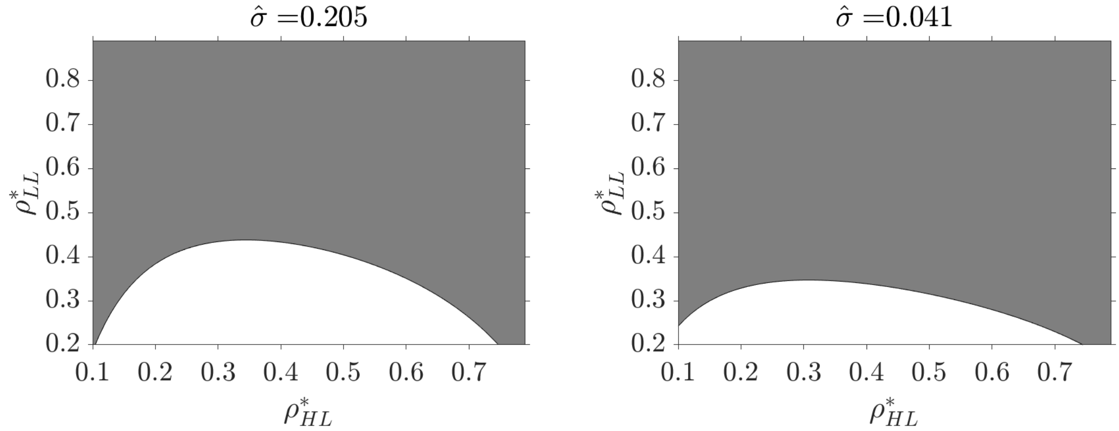

Figure 3: Varying Selected Unconditional Transition Probabilities This area plot shows the percentage difference in the response of loan supply to a sudden increase in uncertainty between the low and the high uncertainty state for various parameter values. Areas shaded in gray denote parameter constellations which lead to a larger response in the low uncertainty state compared to the high uncertainty state. Areas in white represent larger responses in the high uncertainty state. The unconditional transition probability for remaining in the low uncertainty state ρ^*_{LL} varies between 0.2 and 0.9, and the prior belief to move from high to low uncertainty ρ^*_{HL} varies between 0.1 and 0.8. The remaining probabilities of reaching the medium or high uncertainty state are given as the residual values: $\rho^*_{iM} = \rho^*_{iH} = 0.5(1 - \rho^*_{iL})$ for $i \in \{L, H\}$. The left panel depicts results for our baseline shock, $\hat{\sigma} = 0.5\,(\sigma_M - \sigma_L) = 0.205$, and the right panel for shock size $\hat{\sigma} = 0.1\,(\sigma_M - \sigma_L) = 0.041$. The uncertainty levels take the values shown in Table 12.

5 Conclusion

We document that the effects of increases in uncertainty on firms' credit conditions depend on the level of uncertainty. Estimations based on firm-level data document that bank credit conditions deteriorate most in response to an increase in business uncertainty when the business outlook of a firm is associated with a low level of uncertainty. Low levels of uncertainty double the negative impact compared to medium levels and nearly triple the effect compared to high levels.

We rationalize our results using a stylized model, in which loan supply negatively depends on the bank's expectations about the future level of a borrower's business uncertainty. Our model predicts an amplified response of bank lending to an uncertainty shock when the borrower operates under low business uncertainty. This non-linear behavior occurs because the uncertainty increase does not conform with the strong prior belief of the bank that the borrower remains in the low-uncertainty environment. Therefore, increasing uncertainty delivers a strong signal for the bank to adjust its expectations, and lending is reduced substantially. The key to this prediction is a strong prior belief that the borrower remains in the low uncertainty state.

In contrast, under high business uncertainty, a low-uncertainty environment in the future tends to be evaluated as quite unlikely. Increasing business uncertainty only confirms the prior belief and reductions in lending are comparatively small. Overall, an increase in uncertainty leads to a large response of lending under low uncertainty, provided that the bank has a strong prior belief that the borrower remains in the low uncertainty state.

Overall, it is a low-uncertainty environment which lays the ground for the most harmful effect of a sudden increase in uncertainty on bank lending, possibly leading to particularly damaging effects for real activity. One implication is that stabilization policies to counter rising uncertainty are most effective when uncertainty is still low.

References

Alessandri, P. and M. Bottero (2020). Bank lending in uncertain times. *European Economic Review*, forthcoming.

Alessandri, P. and H. Mumtaz (2019). Financial regimes and uncertainty shocks. *Journal of Monetary Economics 101*, 31–46.

Angelini, G., E. Bacchiocchi, G. Caggiano, and L. Fanelli (2019). Uncertainty across volatility regimes. *Journal of Applied Econometrics 34*(3), 437–455.

Arellano, C., Y. Bai, and P. J. Kehoe (2019). Financial frictions and fluctuations in volatility. *Journal of Political Economy 127*(5), 2049–2103.

Bachmann, R., B. Born, S. Elstner, and C. Grimme (2019). Time-varying business volatility and the price setting of firms. *Journal of Monetary Economics 101*, 82–99.

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.

Baetschmann, G., K. E. Staub, and R. Winkelmann (2015). Consistent estimation of the fixed effects ordered logit model. *Journal of the Royal Statistical Society, Series A 178*, 685–703.

Balleer, A., N. Hristov, and D. Menno (2017). Financial constraints and nominal price rigidities. CEPR Discussion Paper No. 11790.

Barraza, S. and A. Civelli (2019). Economic policy uncertainty and the supply of business loans. Universidad de San Andres Working Paper No 134.

Bijsterbosch, M. and P. Guérin (2013). Characterizing very high uncertainty episodes. *Economics Letters 121*(2), 239–243.

Bloom, N. (2014). Fluctuations in uncertainty. *Journal of Economic Perspectives 28*(2), 153–176.

Bloom, N., I. Alfaro, and X. Lin (2019). The finance uncertainty multiplier. Stanford Mimeo.

Boot, A. W. (2000). Relationship banking: What do we know? *Journal of Financial Intermediation 9*(1), 7–25.

Bordo, M. D., J. V. Duca, and C. Koch (2016). Economic policy uncertainty and the credit channel: Aggregate and bank level U.S. evidence over several decades. *Journal of Financial Stability 26*, 90–106.

Buch, C. M., M. Buchholz, and L. Tonzer (2015). Uncertainty, bank lending, and bank-level heterogeneity. *IMF Economic Review 63*(4), 919–954.

Caggiano, G., E. Castelnuovo, and J. M. Figueres (2017). Economic policy uncertainty and unemployment in the United States: A nonlinear approach. *Economics Letters 151*, 31–34.

Caggiano, G., E. Castelnuovo, and N. Groshenny (2014). Uncertainty shocks and unemployment dynamics in U.S. recessions. *Journal of Monetary Economics 67*, 78–92.

Caggiano, G., E. Castelnuovo, and G. Nodari (2017). Uncertainty and monetary policy in good and bad times. Bank of Finland Discussion Paper 8/2017.

Caggiano, G., E. Castelnuovo, and G. Pellegrino (2017). Uncertainty-driven comovements in booms and busts: A structural interpretation. Monash University Mimeo.

Cameron, A. C. and P. K. Trivedi (2005). *Microeconometrics: methods and applications.* Cambridge university press.

Castelnuovo, E. (2019). Domestic and global uncertainty: A survey and some new results. CESifo Working Paper No. 7900.

Christiano, L., R. Motto, and M. Rostagno (2014). Risk shocks. *American Economic Review 104*(1), 27–65.

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

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 21*, 107–179.

Deutsche Bundesbank (2014). An international comparison of the importance of bank credit as a debt financing instrument for non-financial corporations. *Monthly Report 42*, 42–43. November.

Dibiasi, A. (2019). Non-linear effects of uncertainty. Bolzano Mimeo.

European Central Bank (2019). Survey on the access to finance of enterprises in the euro area, April to September 2019. Technical report. Frankfurt.

Fidrmuc, J. and C. Hainz (2013). The effect of banking regulation on cross-border lending. *Journal of Banking and Finance 37*(5), 1310–1322.

Fidrmuc, J., C. Hainz, and W. Hoelzl (2017). Dynamics of access to credit and perceptions of bank lending policy: Evidence from a firm survey. VfS Annual Conference 2017 Mimeo.

Fiore, F. D. and H. Uhlig (2011). Bank finance versus bond finance. *Journal of Money, Credit and Banking 43*(7), 1399–1421.

Gilchrist, S., J. Sim, and E. Zakrajšek (2014). Uncertainty, financial frictions, and investment dynamics. NBER Working Paper No. 20038.

Gilchrist, S. and E. Zakrajšek (2012). Credit spreads and business cycle fluctuations. *American Economic Review 102*(4), 1692–1720.

Grimme, C. (2019). Uncertainty and the cost of bank vs. bond finance. CESifo Working Paper No. 7456.

Hannan, T. H. and A. N. Berger (1991). The rigidity of prices: evidence from the banking industry. *American Economic Review 81*(4), 938–945.

Huber, K. (2018). Disentangling the effects of a banking crisis: Evidence from German firms and counties. *American Economic Review 108*(3), 868–898.

IBS-IND (2015). Ifo business survey industry 1/1980 – 12/2015. LMU-ifo Economics & Business Data Center, Munich.

Jackson, L. E., K. L. Kliesen, and M. T. Owyang (2020). The nonlinear effects of uncertainty shocks. *Studies in Nonlinear Dynamics & Econometrics*, forthcoming.

Klein, M. A. (1971). A theory of the banking firm. *Journal of Money, Credit and Banking 3*(2, Part 1), 205–218.

Lhuissier, S. and F. Tripier (2019). Regime-dependent effects of uncertainty shocks: A structural interpretation. Banque de France Working Paper No. 714.

Link, S. (2020). Harmonization of the Ifo business survey's micro data. *Journal of Economics and Statistics 240*(4), 543–555.

Mumtaz, H. and K. Theodoridis (2018). The changing transmission of uncertainty shocks in the U.S. *Journal of Business and Economic Statistics 36*(2), 239–252.

Nodari, G. (2014). Financial regulation policy uncertainty and credit spreads in the U.S. *Journal of Macroeconomics 41*, 122–132.

Raunig, B., J. Scharler, and F. Sindermann (2017). Do banks lend less in uncertain times? *Economica 84*(336), 682–711.

Salzmann, L. (2020). The impact of uncertainty and financial shocks in recessions and booms. Kiel Mimeo.

Strasser, G. (2013). Exchange rate pass-through and credit constraints. *Journal of Monetary Economics 60*, 25–38.

Townsend, R. M. (1979). Optimal contracts and competitive markets with costly state verification. *Journal of Economic Theory 21*, 265–293.

Valencia, F. (2017). Aggregate uncertainty and the supply of credit. *Journal of Banking & Finance 81*, 150–165.

Appendix

A Details On The Ifo Data

Industry Sector	Number Of Employees 0 –19	20 – 99	100 – 999	≥ 1000
Food and tobacco	19.0	37.0	35.8	8.2
Textile products	6.1	33.0	54.1	6.8
Leather	12.1	39.3	42.2	6.5
Cork and wood products	31.0	45.2	19.9	3.9
Furniture and jewelery	9.6	32.5	53.1	4.8
Paper and publishing	14.7	42.4	38.8	4.1
Elect. and opt. equipment	7.3	28.4	49.2	15.1
Chemical products	10.5	26.1	42.3	21.1
Rubber and plastic	12.7	41.0	38.4	7.9
Other non-metallic products	12.9	35.2	45.4	6.4
Metal products	9.0	31.5	43.6	15.8
Machinery and equipment	4.6	26.1	53.7	15.7
Transport equipment	2.7	11.5	41.7	44.2

Table A.1: Frequency Of Observations. In the first four columns, the table provides the shares of observations in each industry sector for sub-samples of different firm sizes.

B Firm-Level Variables In The Ifo Data

Variable	Question	Response Categories		
Business Situation	We evaluate our business situation with respect to XY as ...	good	satisfactory	unsatisfactory
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 unfavorably
Expected Employees	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

Table B.2: Ifo Questionnaire. The table provides the translated questions and response possibilities of the Ifo survey for manufacturing. For the production questions firms are explicitly asked to ignore differences in the length of months or seasonal fluctuations. Employment Expectations are surveyed every month since July 1997.

C Fixed Effects Ordered Logit Estimation

Dependent Variable: Credit Conditions $fc_{i,t}$		
	(1)	(2)
Uncertainty α_0	0.341***	0.304***
	(0.107)	(0.106)
Uncertainty low α_1	0.276***	0.282***
	(0.087)	(0.086)
Uncertainty high α_2	-0.097**	-0.086*
	(0.048)	(0.048)
Statebus		-0.414***
		(0.042)
Expbus		-0.150***
		(0.033)
Expempl		-0.187***
		(0.049)
No. of obs.	78,338	77,947
Pseudo R-Squared	0.12	0.13

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C.3: Robustness: Fixed Effects Ordered Logit The table reports coefficients; clustered (by firm) standard errors in parentheses; estimated using a panel fixed effects ordered logit model based on Baetschmann et al. (2015). Included in all models but not shown in the table are time-fixed effects for each month and a constant. Model (2) includes, in addition, all firm-specific variables described in Section 3.1. Uncertainty regimes *low* and *high* cover the 16% lowest and highest observations at the firm level for uncertainty. The dependent variable is categorical and equals -1 if a firm perceives lending terms as accommodative, 0 for normal, and +1 for restrictive perceptions.