Measurement and Properties of Firms’ Subjective Uncertainty

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To my parents, Rosemarie and Winfried Lautenbacher.

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Preface

Uncertainty about the future accompanies economic decisions every day. For instance, managers in firms need to estimate the returns on new investments without knowing the future demand for their products. Households may take into account the odds of losing employment when considering the purchase of a car or real estate. The fact that the future is uncertain raises a number of questions. Most importantly, does uncertainty affect economic decisions, and if so, how? What are possible effects on the aggregate economy? Research in this area faces the challenge that uncertainty is not directly observable. Therefore, adequately capturing individuals' beliefs is a key prerequisite for all further investigations.

This thesis addresses the measurement of firms' subjective uncertainty and studies its properties. Before further clarifying my contribution and summarizing the main results, I provide an overview of the related literature.

Conceptually, uncertainty can either take the form of risk or of Knightian uncertainty, which is also known as ambiguity. This distinction dates back to Frank Knight's 1921 book "Risk, Uncertainty and Profit". While, in his words, risk was a "quantity susceptible to measurement", ambiguity was "distinctly not of this character" (Knight, 1921). In modern economics, risk refers to a situation in which an individual can form probabilistic expectations about a set of future events. Ellsberg (1961) demonstrates that there can be situations in which individuals are unable to provide a subjective probability distribution. This characterizes Knightian uncertainty in today's understanding. Due to its more tangible properties, the subsequent theoretical literature has mostly modeled uncertainty as risk.

In an influential contribution, Bernanke (1983) connects uncertainty about investment decisions to aggregate economic fluctuations. The underlying theoretical mechanism is based on so-called "real options": if it is costly to reverse decisions, uncertainty can make it beneficial for investors to delay investments and pause hiring and firing until more information is available. This exploits the option value of waiting (see also, for instance, McDonald and Siegel 1986). Another classical channel that connects uncertainty to decisions that lead to a negative impact on the economy is precautionary behavior. This can materialize in lower consumption spending by households and reduced investment by risk-averse managers. A third channel works via increased risk premia, which increase the cost of finance and depress demand. Moreover, there are two theoretical mechanisms that postulate an increase in (longer-run) growth as a result of increased uncertainty. Since losses are bounded, but gains are not, the theory of "growth options" predicts higher investment as expected profits increase with higher risk. Similarly, if profits are convex in demand or costs, a higher variance of future outcomes may also incentivize investment according to the Oi-Hartman-Abel effect. Bloom (2014) provides an overview of these channels.

After the experience of the Great Recession, there has been a surge in the interest to study economic uncertainty and its effects on the business cycle. Motivated by the Global Financial Crisis as well as earlier events such as the 9/11 terrorist attacks and the OPEC I oil crisis, the notion of aggregate uncertainty shocks as potential drivers of the business cycle gained momentum in macroeconomics. This is reflected in a number of theoretical and empirical contributions following the seminal work by Bloom (2009).

On the theoretical side, canonical business cycle models were augmented to investigate the effect of time-varying uncertainty. For instance, Basu and Bundick (2017) illustrate the dampening effect of uncertainty caused by a precautionary decrease in consumption coupled with downward price rigidities. Some scholars study an increase in the variance of technology shocks in combination with non-convex adjustment costs and investigate the effects on the real economy and the labor market (Bloom et al., 2018b; Schaal, 2017). Others point at financial distortions as a transmission channel of uncertainty to output (see, for instance, Gilchrist et al. 2014). Most studies assume that uncertainty shocks are exogenous. This is challenged by some scholars who lay out theoretical feedback effects from lower growth to uncertainty, such as Fajgelbaum et al. (2017). In most models uncertainty refers to risk, which is often equated with volatility. A prominent exception is Ilut and Schneider (2014), who introduce Knightian uncertainty to this line of research. They explain aggregate fluctuations of the economy using confidence shocks and behavioral insights about ambiguity aversion.

In the empirical literature, the notion of uncertainty shocks inspired the development of various time series proxy measures of uncertainty. Popular examples include the implied or realized volatility of stock prices (e.g. Bloom 2009), the cross-sectional dispersion of firm variables (e.g. Bachmann et al. 2013), the conditional volatility of macroeconomic forecast errors (Jurado et al., 2015), and count indices of uncertainty-related keywords in newspapers (Baker et al., 2016). While all of these proxies refer to the concept of uncertainty, they are statistically quite distinct (Kozeniauskas et al., 2018). A common stylized fact is that they are counter-cyclical: uncertainty is higher in recessions. Using time series econometric methods, innovations in proxy measures of uncertainty are generally found to have a negative effect on output. Based on proxies derived from the stock market, Berger et al. (2020) show that realized volatility is associated with declines, while forward-looking conditional volatility is not. Ludvigson et al. (2020) distinguish financial from macroeconomic uncertainty and find negative effects on output only for shocks originating in the financial sector. They also emphasize the difficulty to identify uncertainty shocks in time series models, as they may be endogenous to first moment shocks.

In summary, the empirical evidence on the effects of uncertainty using macroeconomic proxy measures remains suggestive. The two main obstacles to a clearer picture are imprecise measurement and possible endogeneity of uncertainty and growth. Simultaneity and feedback effects are generally difficult to address and pose a big challenge to all analysis attempting to causally link uncertainty to outcomes. Concerning measurement, a shortcoming of all macroeconomic proxies for uncertainty—and the results of the analyses using them—is that they may differ from the perceived uncertainty of individuals in the economy. When studying the effect of uncertainty on outcomes, what should ultimately matter, besides a transmission via risk premia in financial markets, is the subjective uncertainty of decision makers.

As an alternative to time series econometric analyses, micro data can be used to test the theoretical channels that link uncertainty to economic decisions and outcomes. However, due to the scarcity of data on subjective uncertainty, this literature is small. One rare example is Guiso and Parigi (1999). Based on a cross section of Italian firms, they find that businesses that are more uncertain about their future sales growth plan to invest less. Ben-David et al. (2018) present evidence that, when more uncertain, households exhibit precautionary behavior regarding consumption, credit, and investment.

One reason for the lack of micro data and time series of subjective uncertainty is the rational expectations paradigm. It has dominated economists' thinking since its promotion in the 1970s. As a convenient feature in modeling, it entails that agents are assumed to be fully informed and to hold rational expectations in accordance with the model (Coibion et al., 2018a). Another reason for the lack of micro data on subjective uncertainty is the behaviorist tradition to only take into consideration individuals' actions and outcomes, but not their intentions and perceptions (Bachmann, 2019).

With the rise of behavioral economics, psychological insights were introduced into mainstream economics and weakened the paradigm of rational expectations. As a result, in the last decade there has been renewed interest in survey data about the expectations and uncertainty of households and firms. In fact, there exists a long tradition of eliciting expectations in regular consumer and business surveys to inform macroeconomic forecasts. However, only in recent years researchers have started to systematically exploit this existing information, to design new surveys, and to add questions about subjective uncertainty. Micro data on perceptions opens up new opportunities to review model assumptions and to test the theoretical channels that describe effects of uncertainty on economic outcomes. To date, we still know little about the determinants and properties of subjective business uncertainty, and its effect on economic decisions and the business cycle.

This dissertation addresses some of these gaps. It consists of three chapters—each constitutes a self-contained research article and can be read independently. The papers that underlie chapters one and two are co-authored with Rüdiger Bachmann, Kai Carstensen, and Martin Schneider. The third chapter is my own work. Based on German firm-level survey data collected by the ifo Institute, this thesis extends the literature by presenting three new measures of managers' perceived business uncertainty and by providing an extensive analysis of their properties. In particular, it examines the relation of firms' subjective uncertainty to past growth, firm characteristics, volatility, expectations, and corporate decisions. Moreover, it studies the prevalence of Knightian thinking. Below, I briefly summarize the main findings of each chapter.

The first chapter examines the relationship between firms' subjective uncertainty and past change, and it compares subjective uncertainty to measures of realized and conditional volatility in the cross section and the time series. We measure uncertainty as the difference between managers' expectations about quarterly sales growth in the best and in the worst case. Our main finding is that uncertainty reflects change: firms report more subjective uncertainty after either high or low growth realizations. In the cross section of firms, subjective uncertainty differs from statistical measures of uncertainty such as volatility: fast-growing and large firms report lower subjective uncertainty than fast-shrinking and small firms, respectively, even if they face shocks of similar size. By contrast, the substantial time variation in firm-specific subjective uncertainty resembles that in conditional volatility: both measures of uncertainty are mildly persistent and rise more when growth is temporarily low. These results highlight the importance of idiosyncratic variation in uncertainty outside recessions and provide micro evidence for feedback effects between uncertainty and growth. Moreover, they entail valuable insights for models of firm dynamics and those using conditional volatility as a proxy for subjective uncertainty.

The second chapter investigates whether decision-makers in firms think about the future in terms of probabilities. We ask German manufacturing executives about the likelihood of a sales increase. The key departure from existing business surveys is that we do not force respondents to submit a single probability, but instead give a "Knightian" option of answering with a probability interval. Our main result is that Knightian responses are pervasive: 76% of firms choose a probability interval at least once in five years. We further show that Knightian responses are motivated by a lack of clarity about the future; they do not reflect a lack of sophistication. Over time, substantial switching into and out of the Knightian state reflects both idiosyncratic and aggregate shocks. In particular, the share of Knightian responses spikes up sharply during the Greek crisis in 2015, along with credit spreads. This chapter establishes new stylized facts about the probabilistic beliefs of top-level managers in firms, as opposed to participants in behavioral laboratory experiments. Given the common practice to elicit subjective uncertainty using single probabilities—uncertainty is then measured, in effect, as risk—the new findings may contribute to adopt more flexible question types that also incorporate Knightian thinking.

The third chapter presents a novel measure of subjective uncertainty and relates it to business expectations and firm decisions. Uncertainty is measured by asking managers directly how uncertain they are about their future business development. I demonstrate that the relationship between perceived uncertainty and expectations is strongly negative at the micro level and almost perfectly inverse in the aggregate. It is also state-dependent: uncertainty co-moves less with expectations in bad times. These stylized facts are manifest during the economic downturn of the COVID-19 crisis, but also in the years before. They highlight the simultaneity of movements in subjective uncertainty and expectations, which impedes the identification of uncertainty shocks in time series econometric analyses. As an alternative approach, I use micro data to evaluate the connection of subjective uncertainty and expectations to corporate decisions about investment and employment. In particular, I exploit the between-firm variation during the COVID-19 shock. In contrast to first moment changes, I find that changes in uncertainty neither predict the postponement of investment nor a "freeze" of employment. Averaging over all firms, these results are not in accordance with "wait and see" behavior that we would expect from the "real options" channel of uncertainty.

Chapter 1

Uncertainty and Change: Survey Evidence of Firms' Subjective Beliefs*

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* This chapter is based on joint work with Kai Carstensen, Rüdiger Bachmann, and Martin Schneider.

1.1 Introduction

A large theoretical literature studies how firms respond to time variation in uncertainty. It has highlighted two key sources of variation. First, firms respond in the short run to news about the business environment. For example, in recessions firms may become less confident in their forecasts of future cost or demand. Heightened uncertainty can then have a negative impact on their hiring and investment.[1] Second, many firms face longer term risks that they learn about over time: for example, expanding firms find out gradually about demand in new markets. It makes sense for firms that operate in unfamiliar territory to operate more cautiously; to an observer they may then appear to adjust "too slowly".[2]

Yet, to date there is little *direct* evidence on how decision makers within businesses perceive and process uncertainty. Instead, subjective uncertainty is often indirectly inferred through the lens of a particular model: for example, if a model imposes rational expectations, the realized volatility of shocks estimated by the modeler becomes a measure of uncertainty perceived by the firms. However, since there is no consensus on model structure, many open questions remain. In particular, how much does subjective uncertainty fluctuate over time? How is it shaped by past firm performance, both in the short run and the longer run? And how does it relate to realized volatility?

This paper provides survey evidence on firms' perceived uncertainty about future sales growth. We introduce a panel data set of firms' subjective beliefs, characteristics and performance for the German manufacturing sector. It is based on a new module of the ifo Business Survey, a long-established survey used to develop business sentiment indicators. The survey is well regarded in the German business community: questions are answered mostly by senior management and there is a high response rate even from large firms.[3] Our data set is based on 14 survey waves in consecutive quarters from 2013 to 2016. We use it to document how subjective uncertainty varies not only in the cross section of firms but also over time.

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[1] Bloom (2014) and Fernández-Villaverde and Guerrón-Quintana (2020) survey the macroeconomic literature on fluctuations in uncertainty. One concrete workhorse model assumes that productivity exhibits stochastic volatility that – exogenously or endogenously – increases at the beginning of recessions.

[2] Following the seminal work of Jovanovic (1982), a large literature on firm dynamics with learning studies questions such as the contribution of young firms to growth and the role for subsidizing such firms.

[3] Research studies using the standard ifo expectation data are, for instance, Bachmann et al. (2013); Buchheim and Link (2017); Massenot and Pettinicchi (2018); Bachmann et al. (2019); Enders et al. (2019a,b).

The new survey module asks firms for a forecast of one-quarter-ahead sales growth together with two numbers for best and worst case sales growth scenarios. We then define the difference, that is, *span*, between the best and worst case one-quarter-ahead sales growth scenarios as our quantitative measure of subjective uncertainty. The idea behind the survey design is that firms can directly report scenarios developed as part of their regular planning process. Responses to a one-time meta survey we commissioned show that a large majority of firms engages in scenario analysis and uses results from routine quantitative planning when filling out the survey module. Since in addition to the forecast we also retrospectively ask for firms' realized sales growth, we can further compare subjective uncertainty to firms' realized (subjective) forecast errors.

Our main finding is that *uncertainty reflects change* experienced by firms. This principle describes beliefs in both the short and longer run. On the one hand, subjective uncertainty perceived by an individual firm varies substantially at the quarterly frequency; in particular, it is high after both very good and very bad growth realizations. This short run pattern is shared by the conditional volatility of firms' forecast errors. On the other hand, average subjective uncertainty over our four-year sample comoves strongly with measures of change in a firm's environment: it is higher for firms that consistently grow or shrink, as well as for firms with more volatile sales growth. In the cross section of firms, however, subjective uncertainty behaves differently from realized volatility. In particular, large and growing firms report relatively low subjective uncertainty even when they make large forecast errors.

Our results thus provide direct evidence for both types of time variation in uncertainty emphasized in the literature. One key takeaway is the importance of short run *idiosyncratic* variation. Mechanisms at work when uncertainty goes up in recessions could therefore be relevant also for firm dynamics in normal times. Moreover, subjective uncertainty is closely related in the short run to the (absolute) magnitude of past and future shocks. A model of short term planning should therefore draw a connection between subjective uncertainty and conditional volatility, for which our results provide an empirical basis. Traditionally, this connection was simply assumed through the rational expectations assumption. Firms' planning under uncertainty appears to reflect at least in part actual volatility, perhaps because managers are quite familiar with the short run dynamics of their business.

At the same time, our results point to an important role for learning over the longer run. Indeed, fast-growing and fast-shrinking firms not only perceive higher uncertainty, but also make forecasts that are too conservative, that is, systematically biased towards zero. This is true after controlling for firm size, suggesting that even large firms sometimes enter unfamiliar territory where growth is uncertain and hard to forecast. While we document a connection between volatility and subjective uncertainty also for longer term risk, there is an important second force: successful firms – either growing or large – report lower uncertainty when faced with the same volatility. This fact is consistent with mechanisms that make uncertainty matter more to decision makers in bad times, so their planning considers a wider span of scenarios.

To provide an idea of magnitudes, the mean span between best and worst case scenarios is 12.1 percentage points (pp), slightly above the mean absolute forecast error. Firms differ in average subjective uncertainty: the cross sectional standard deviation of average span per firm is 7.4 pp. At the same time, we document large time variation in subjective uncertainty for individual firms: the cross sectional average of the firm-level standard deviation of span is 5.9 pp. Time varying span is thus a volatile component of firms' planning process. In fact, it is almost as volatile as the usual driver of firm planning in economic models, namely changes in conditional expectations: the average firm-level time series standard deviation of growth forecasts is 7.4 pp. Most of the time series variation in subjective uncertainty is firm-specific: time-sector fixed effects explain only a negligible share.

Our cross-sectional results relate average firm-level subjective uncertainty to two measures of how a firm's environment changes over the medium term. First, we define *trend* as a firm's unconditional mean growth rate over our four year sample. We show that both high and low trend firms are significantly more uncertain. Span in the bottom quartile by trend is 6pp higher than for the "normal" firms, that is, firms within the interquartile range; it is 2pp higher in the top quartile. At the same time, high and low trend firms' forecasts are biased towards zero by about 5pp on average. Both results are consistent with models of learning: fast expansion or shrinkage leads firms to a less familiar, and hence more uncertain, state of business that is difficult to forecast. They are not consistent with simple models of firm dynamics in which every firm knows its trend growth.

Our second measure of medium term change is *turbulence*, defined as firms' in-sample sales growth volatility over time. High turbulence firms face larger (absolute) shocks than the average firm, but do not make biased forecasts. Moreover, they not only report higher subjective uncertainty on average, but also higher *variation* in subjective uncertainty. Indeed, controlling for trend as well as size, the mean span in the top quartile by turbulence is 10pp higher than in the bottom quartile, whereas the standard deviation of span is 6pp higher. In other words, planning at firms that face larger shocks not only uses scenarios that are further apart but also varies those scenarios more over time as shocks arrive.[4]

The short-run relationship between subjective uncertainty and past growth is V-shaped, with a minimum close to zero. Firms thus become more uncertain after either negative or positive growth. Bad quarters increase uncertainty by more: while a one percentage point lower negative growth rate is followed by 30 basis points wider span between firms' best and worst case scenarios, a one percentage point higher positive growth rate widens span by only 17 basis points; these numbers are robust to controlling for firm heterogeneity. The V-shape is perhaps surprising in light of the negative comovement between growth and uncertainty emphasized in the literature. It is nevertheless consistent because this literature focuses on the behavior of uncertainty over the business cycle, whereas most variation in our sample is idiosyncratic. Our results suggest that individual firms' uncertainty is shaped by its individual performance, and increases when an unfamiliar event occurs, especially a bad one.

There are several candidate explanations for why uncertainty might reflect change in the short run. One possibility is that the basic principle we have found in the cross section – firms that operate in unfamiliar territory perceive more uncertainty – is also at work in the short run. If this force were dominant, we should see that uncertainty is particularly related to growth *surprises*. We indeed confirm a positive relationship between lagged absolute forecast errors and span. However, we also show that, in firm quarters with negative growth, the previous-quarter growth rate is a sufficient statistic for predicting span given the previous-quarter growth rate and forecast error. The reason behind this result is that predictable low growth realizations also increase uncertainty, to a similar extent as low growth surprises. A possible explanation is that planning takes into account state variables other than growth. For example, in a model with customer capital, a shrinking firm might see the size and/or composition of its future pool of customers become more uncertain in a predictable way.

How does firms' subjective uncertainty compare to the volatility of their forecast errors, a measure of uncertainty in many models? Our key cross sectional finding here is that successful firms—defined as either large and fast-growing—plan with narrower spans even when they face the same magnitude of forecast errors as less successful firms. The result has two parts. First, controlling for firm size, the absolute forecast

[4] This distinction matters because of its implication for behavior such as firm factor choice: in the presence of adjustment costs or time to build, time variation in subjective uncertainty leads firms to respond differently each period. If instead, high volatility firms simply faced larger iid shocks, they might still behave different from low volatility firms, but that behavior would not vary over time. Our results say that the theoretical mechanisms that make firms respond to uncertainty generate both cross sectional and time series variation.

error for growing firms is 2.5pp higher than for firms that are neither growing nor shrinking, while span is not significantly different. By contrast, compared to stable firms both the absolute forecast errors and span increase by about the same amount of roughly 3pp for shrinking firms. While high and low trend firms are both in unfamiliar territory—in the sense of facing larger shocks—growing firms do not adjust their planning. Second, large firms with more than 250 employees make similar absolute forecast errors as smaller firms, yet plan with spans that are up to 5pp narrower, controlling for trend and turbulence. Size by itself thus also leads firms to plan with narrower spans.

How does time variation in subjective uncertainty compare to that in conditional volatility? This question is more difficult to answer: it is no longer sufficient to compare absolute forecast errors to a measure of subjective uncertainty, as we did when examine the cross section. Indeed, computing the variance of forecast errors delivers an *unconditional* measure of volatility. The relevant counterpart we are looking for here is the predictable component of volatility. We want to establish whether conditional volatility is persistent and related to past growth in a similar way to span. We thus utilize the panel dimension of our data set to estimate dynamic panel regressions for both our subjective uncertainty measure span as well as panel GARCH models for firms' subjective forecast errors.

The short-run dynamics of firm-specific subjective uncertainty closely resemble that of the conditional volatility of shocks experienced by firms: both are mildly persistent, increase with bad past growth and increase somewhat less with good past growth. We take away that, at least in the short run, firms adjust their planning process based on the experience that high and—even more so—low growth signals larger future surprises. In applications that emphasize the short run, an approach that equates uncertainty with conditional volatility thus describes actual firm planning quite well.

Our study is motivated by a large body of work on firm behavior under uncertainty. Theory has proposed a number of mechanisms through which uncertainty impacts input choices that have to be made before cost or demand is fully known. Examples include wait-and-see effects or financial frictions that increase the cost of capital when uncertainty is high. While the relevant theoretical concept is subjective uncertainty, empirical tests have long had to rely on proxy measures.[5] Following the pioneering

[5] Empirical work with micro data on firms tends to rely on proxy measures for uncertainty such as the volatility and dispersion of stock returns (Leahy and Whited, 1996; Campbell et al., 2001; Bloom et al., 2007) or other firm-level outcomes (Bachmann and Bayer, 2013, 2014; Jurado et al., 2015; Bloom et al., 2018b), implied options volatility (Bloom, 2009; Barrero et al., 2017), perceived political uncertainty from quarterly earnings conference calls (Hassan et al., 2019), and qualitative (Bachmann et al., 2013)

work of Guiso and Parigi (1999), a small number of studies have used survey measures of uncertainty to investigate its effects on economic activity (see in particular, Bontempi et al., 2010; Dibiasi et al., 2018; Bloom et al., 2019). The goal of the present paper is not to study the effect of uncertainty on outcomes, but instead to characterize how uncertainty varies over time, and in particular how it relates to past outcomes.

In particular, our short run results provide new evidence to guide an active discussion about the relationship between uncertainty and growth. Following Bloom (2009), a growing literature has incorporated uncertainty shocks into macroeconomic models.[6] Such shocks are often orthogonal to first moment shocks, for example, higher uncertainty lower current growth even if it is unrelated to past growth. More recently, several papers have considered feedback effects from growth to uncertainty (Bachmann and Moscarini, 2012; Fajgelbaum et al., 2017; Ilut and Valchev, 2017; Ilut et al., 2018; Baley and Blanco, 2019; Berger and Vavra, 2019; Ludvigson et al., 2020). One of our main results is the strong association of high uncertainty with low or high past growth. It implies that feedback effects – or possibly correlated shocks – are particularly important for understanding the comovement of growth and subjective uncertainty.

Firm-level idiosyncratic uncertainty is also a key building block for models of firm dynamics that aim to explain the size distribution of firms, the (mis)allocation of factors of production and ultimately the level and growth rates of aggregate output (see surveys by Luttmer 2010 or Hopenhayn 2014; for recent examples, see contributions by Pugsley et al. 2018 and David and Venkateswaran 2019). Our direct evidence on long-term risks is consistent with the mechanisms explored in quantitative models of firm learning such as Abbring and Campbell (2003), Eaton, Eslava, Kugler and Tybout (2012) or Arkolakis et al. (2018). Moreover, our results on high frequency variation in subjective uncertainty suggest that even a short time-to-build friction could give rise to effects of uncertainty on factor choice. Indeed, with any type of adjustment cost, quarterly variation in uncertainty will work like a distortion—a wedge between the marginal product and price of a factor (see, for example, Ilut and Saijo 2020 for a model of firms facing idiosyncratic risk that clarifies this feature).

The new ifo survey module is one of a handful of data sources on expectations of leading decision makers in firms about their own economic circumstances.[7] Bloom

as well as quantitative (Bachmann et al., 2017, 2019; Altig et al., 2019; Bloom et al., 2019) firm-level forecast errors obtained from surveys.

[6] An incomplete list is: Christiano et al. (2014); Gilchrist et al. (2014); Fernández-Villaverde et al. (2015); Basu and Bundick (2017); Arellano et al. (2019).

[7] There is also an active literature that studies firm expectations about aggregate variables, such as inflation (see, for New Zealand, Kumar et al. 2015; Coibion et al. 2018b, and for Italy, Coibion et al. 2020) and GDP (see, for Japan, Tanaka et al. 2019).

et al. (2017) and Altig et al. (2019) present results from a new business survey of top managers in US businesses, administered by the Census at the annual frequency and the Federal Reserve Banks of Atlanta at the monthly frequency. They also document a V-shaped relationship between growth and uncertainty in the cross section. They do not study time variation in subjective uncertainty, which is the main focus of our paper. Another source of data is the panel of chief executives' stock return expectations assembled by John Graham and Campbell Harvey at Duke University. Ben-David et al. (2013) show that managers are strongly miscalibrated in that their subjective forecast densities are too narrow, thus questioning rational expectations as a modeling assumption. Gennaioli et al. (2016) show that managers' expectations are connected to actual firms' investment plans, thus showing that miscalibration has real effects. Our results confirm the presence of systematic forecast errors by firms that experience a lot of change. Moreover, the perception of uncertainty deviates from volatility for successful firms.

The paper is structured as follows. Section 2 explains our new survey questions and properties of the data. Section 3 introduces the raw relationship between uncertainty and change and presents a simple organizing framework. Section 4 studies uncertainty and change in the cross section, while Section 5 looks at time series variation after controlling for fixed firm characteristics. Section 6 compares the dynamic properties of subjective uncertainty and statistical measures of uncertainty.

1.2 Data

The ifo Business Survey, run by the Munich-based ifo Institute, is a long-running survey of German businesses. Despite the occasional attrition, the ifo Institute maintains a sample that is representative of the German manufacturing sector by replacing exiting firms with new respondents (see Sauer and Wohlrabe 2020). The responses from the survey provide input for a leading indicator of the German business cycle, the ifo Business Climate Index. The latter is part of the EU-harmonized business surveys commissioned by the Directorate General for Economic and Financial Affairs of the European Commission.[8]

[8] Aggregate survey results for Germany are presented at www.ifo.de/w/3fvxPxj2P, the harmonized European results, including the European Economic Sentiment Indicator, can be found here: https://ec.europa.eu/info/business-economy-euro/indicators-statistics/economic-databases/business-and-consumer-surveys_en.

In 2012, we designed an online module of quantitative questions to elicit subjective firm uncertainty that were asked to all manufacturing firms in the main survey. An initial pilot wave in December 2012 was met by strong interest. Analysis of text comments submitted by firms further showed that firms had no trouble understanding the questions. The module has now been in the field since 2013, with participation remaining stable between 300 and 400 firms per wave.[9]

A firm in the survey is either a stand-alone firm or a division of a large conglomerate. For simplicity, we refer to "firms" throughout this paper. The survey questions are about growth in sales. The German term used in the questionnaire, "Umsatz", is a well-defined technical term in profit and loss accounting, translated into English as "sales" or "total revenue." It is commonly used as an accounting statistic at the levels of both a division and an entire firm.

The survey is administered at the beginning of every quarter. Our current sample uses 14 survey waves spanning 2013:Q2 through 2016:Q3. In addition, in fall 2018, the roughly 400 firms from our baseline sample participated in a one-time meta survey we fielded with questions on how firms collect information and arrive at the views expressed in our uncertainty module. 191 of these firms responded. Furthermore, Sauer and Wohlrabe (2019) documents the identity of the respondents in the ifo Business Survey. Finally, there was an additional meta survey administered by ifo in the fall of 2019 and sent out to all the participants in the ifo main manufacturing survey. For our purposes, this additional meta survey provides information on the regularity of respondents in the survey.

The selection of participants in the uncertainty module is similar to that of the main manufacturing survey (which is designed to be representative of the German manufacturing sector). Indeed, Appendix 1.A shows that it is essentially impossible to predict participation in the uncertainty module using information on firm size, sector, and survey wave. In particular, our data contain a substantial number of large firms: when we measure firm size by the number of employees, the 75th percentile is at about 250 employees. The median firm employs 100 workers while the 25th percentile is at 40.

[9] The raw data can be found under IBS-IND (2016).

1.2.1 Quality of Responses

In partnering with ifo, our goal was to develop a data set that reflects the assessment of uncertainty by key decision makers in firms, and the use of quantitative analysis the firm considers in their actual decision making. Our meta survey together with other meta surveys provides evidence on the quality of the data along these dimensions.

Before turning to the results from our own meta survey, we note that Sauer and Wohlrabe (2019) documents that, in the overwhelming majority of firms in the manufacturing sector, 86%, the respondent is a member of top management: 73% of firms mention the CEO, CFO or COO, whereas 13% of units surveyed refer to a "division head", the natural label for the top executive if the unit surveyed is not a stand-alone firm (see Sauer and Wohlrabe 2019, Table 2). For very large firms with more than 500 employees, the share of responses from top management is only slightly lower than in the population as a whole: a bit over 65% CEO, CFO or COO, and a bit over 15% the division head (see Sauer and Wohlrabe 2019, Figure 1). These findings are consistent with an earlier meta study conducted by ifo about the trade sector (see Abberger et al., 2011). The additional meta survey commissioned by ifo in the fall 2019 further shows that the identity of the responder within the firm changes rarely: 83% of firms indicate the responder is "always the same person"", 15% say "mostly the same person", and less than 2% mention a team of people or that the responder "changes frequently".

Our meta survey from fall 2018 asks firms what type of information they use when they fill out the questionnaire of our module. The questionnaire in the original German is shown in Appendix 1.B. We first ask whether answers to our uncertainty questions are guided by numbers that the firm has already developed in house as part of a regular quantitative planning process. The results are summarized in the top panel of Table 1.1, both for all firms and broken down by size class. On average, 80% of firms respond that they use results from its quantitative planning. The share is remarkably stable across firms, only very small firms with less than 10 employees report a somewhat lower share.

We then add a follow-up question about alternative frameworks for quantitative planning under uncertainty.

If yes, how important were typically results from (i) a scenario analysis around a baseline forecast (ii) statistical analysis (iii) other (please name).

For each of the options (i)-(iii), firms were asked to indicate importance on a four point scale: not important, less important, important, very important. Firms which chose option (iii) were able to fill in an alternative approach.

One goal here was to learn about the use of statistical analysis. Moreover, we were interested in the use of scenario analysis, that is, thinking about the future in terms of a few concrete—often fairly detailed—scenarios without necessarily attaching probabilities. A well-known example of scenario analysis is bank stress testing: banks are asked to forecast losses given a detailed set of contingencies, but they are not asked to assign probabilities to those contingencies. The literature suggests that scenario analysis is common in German businesses.[10]

The middle panel of Table 1.1 summarizes how German manufacturing firms approach quantitative planning. Both scenario analysis and statistical analysis are popular: both methods are rated as at least important by more than half of the firms. We again break down the answers by size. The share of firms that rates each method at least important is increasing in size. Interestingly, large firms rely more heavily on scenario analysis by a substantive margin of 20 percentage points. For firms that routinely compute adverse and favorable scenarios as part of their planning process, filling out the survey does not impose an additional forecasting task and is likely to generate more thought-out answers.

The bottom panel of Table 1.1 speaks to what leaders in German manufacturing firms think about the scenarios we ask them routinely in the main uncertainty module. We gave them two options (plus a verbal other option): are these plausible scenarios that may well occur, or are they scenarios that a possible but extraordinary. In technical language, are these scenarios viewed as (close to) support bounds? The clear majority of firms views scenarios as plausible scenarios rather than support bounds. At the same time, the answers from the middle panel suggest that this is how firms actually think about there uncertain future. We thus view our approach of asking firms about their subjective uncertainty through scenarios as both a flexible and adequate elicitation method.

Finally, we find that conditional on using scenario analysis as "very important" or "important", a majority of firms (56%) values statistical analysis as "less important" or "not important." Conversely, conditional on valuing scenario analysis as "less important" or "not important," 64% of firms are more keen on statistical analysis ("very important" or "important"). This suggests a certain imperfect substitutability between the two quantitative sales planning techniques. As for which firms tend to view scenarios as plausible a opposed to possible but extraordinary events, there does not seem to be a difference between those firms which employ quantitative sales planning tech-

[10] Mietzner (2009) provides an overview of the literature on strategic planning in German firms. In many industries, the majority of firms engage in some sort of scenario analysis.

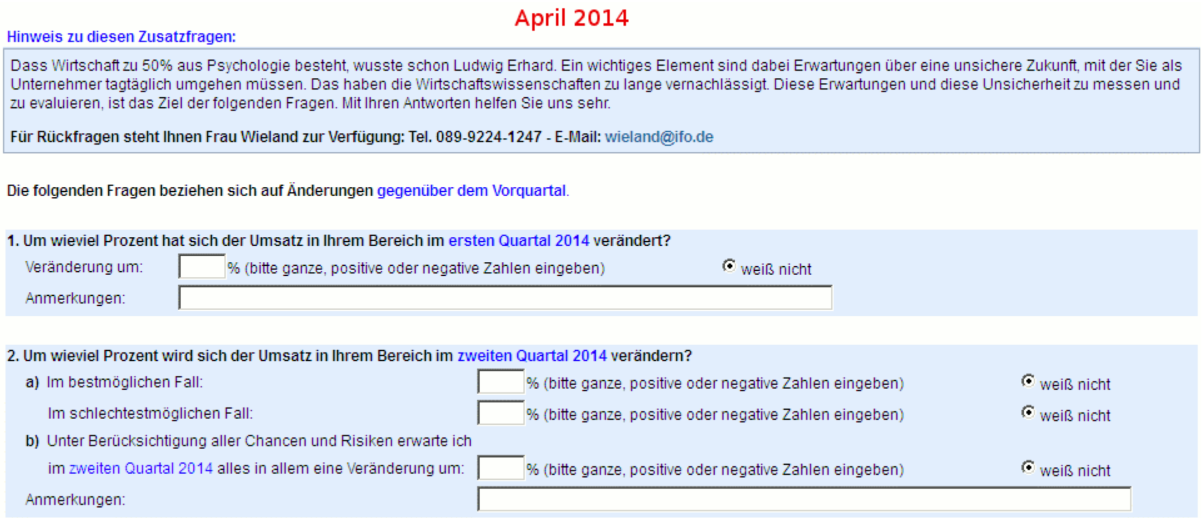
Table 1.1: Meta Survey 2018 answers on quantitative planning

	All obs.	Tiny & Small	Medium	Large
Firms with quantitative sales planning	0.80 (0.03)	0.73 (0.06)	0.80 (0.05)	0.80 (0.04)
Results from scenario analysis				
very important	0.15 (0.03)	0.57 (0.08)	0.68 (0.06)	0.66 (0.07)
important	0.49 (0.04)			
Results from statistical analysis				
very important	0.13 (0.03)	0.52 (0.08)	0.57 (0.07)	0.47 (0.07)
important	0.39 (0.04)			
Selection of scenarios				
Best and worst scenarios are plausible	0.71 (0.03)	0.77 (0.05)	0.67 (0.06)	0.70 (0.06)
Best and worst scenarios are extraordinary	0.29 (0.03)	0.23 (0.05)	0.33 (0.06)	0.30 (0.06)

Notes: The numbers are from the fall 2018 meta survey on a sample of 191 firms. The top panel presents the share of firms that report that their answers to our uncertainty questions are guided by numbers that the firm has already developed in house as part of a regular quantitative planning process. Column 1 reports the overall share, while columns 2 to 4 show the share by three size groups. In line with the definition by the German Statistical Office, firms are “tiny” if the have less than 10 employees, “small” if the number of employees is between 10 and 50, “medium” if the number of employees is between 50 and 250, and “large” if the number of employees exceeds 250. The middle panel contains the results of two follow-up questions for firms that report engaging in regular scenario planning. We present the shares of firms that consider scenario and statistical analysis, respectively, as “very important” and “important” for their quantitative sales planning. The other answer options were “less important” and “not important.” Column 2 to 4 shows the sum of the shares answering with “very important” or “important” by size group. The bottom panel displays the results from a question where we asked firms about how they think about the best and worst case scenarios when answering them in our main survey; the options were plausible scenarios or possible but extraordinary scenarios.

niques and those that do not. We find the same approximate independence for those firms that view statistical analysis as “very important” or “important” versus those that find them “less important” or “not important.” However, firms that find statistical analysis as “very important” or “important” have a very high conditional probability of viewing scenarios as plausible (80%), while those firms for which statistical analysis is “less important” or “not important” this probability shrinks to 58%. This means, the expert firms in scenario analysis are clearly not viewing them as support bounds.

Figure 1.1: Original survey questionnaire in German


April 2014

Hinweis zu diesen Zusatzfragen:

Dass Wirtschaft zu 50% aus Psychologie besteht, wusste schon Ludwig Erhard. Ein wichtiges Element sind dabei Erwartungen über eine unsichere Zukunft, mit der Sie als Unternehmer tagtäglich umgehen müssen. Das haben die Wirtschaftswissenschaften zu lange vernachlässigt. Diese Erwartungen und diese Unsicherheit zu messen und zu evaluieren, ist das Ziel der folgenden Fragen. Mit Ihren Antworten helfen Sie uns sehr.

Für Rückfragen steht Ihnen Frau Wieland zur Verfügung: Tel. 089-9224-1247 - E-Mail: wieland@ifo.de

Die folgenden Fragen beziehen sich auf Änderungen gegenüber dem Vorquartal.

1. Um wieviel Prozent hat sich der Umsatz in Ihrem Bereich im ersten Quartal 2014 verändert?

Veränderung um: % (bitte ganze, positive oder negative Zahlen eingeben) weiß nicht

Anmerkungen:

2. Um wieviel Prozent wird sich der Umsatz in Ihrem Bereich im zweiten Quartal 2014 verändern?

a) Im bestmöglichen Fall: % (bitte ganze, positive oder negative Zahlen eingeben) weiß nicht

Im schlechtestmöglichen Fall: % (bitte ganze, positive oder negative Zahlen eingeben) weiß nicht

b) Unter Berücksichtigung aller Chancen und Risiken erwarte ich im zweiten Quartal 2014 alles in allem eine Veränderung um: % (bitte ganze, positive oder negative Zahlen eingeben) weiß nicht

Anmerkungen:

Notes: Original questionnaire from ifo's online module on subjective uncertainty in German; screenshot from April 2014.

1.2.2 Eliciting Subjective Uncertainty

The uncertainty module of the ifo Business Survey asks firms, at the beginning of a quarter, a two-part question. Figure 1.1 displays the sample questionnaire for April 2014 in the original German. In English, the questionnaire reads:

The following questions refer to changes against the previous quarter.

1. *By how much in percentage terms have your sales changed in the first quarter of 2014?*

2. *By how much in percentage terms will your sales change in the second quarter of 2014?*

   a. *In the best possible case*:
   In the worst possible case:

   b. *Taking into account all contingencies and risks, I expect for the second quarter of 2014 all in all a change of*:

The questionnaire form contains four boxes for respondents to provide their four numerical answers. Next to every box, there is a reminder to provide positive or negative integers. The default option is to skip the question by checking "don't know" ("weiß nicht" in German) behind the box, as shown in the empty form in the figure. Once a respondent enters a number, the "don't know"-option becomes unchecked. Finally, underneath both questions 1 and 2, firms are invited to provide free text comments ("Anmerkungen").

To clarify the timing, consider a firm responding in April 2014, that is, in the first two and a half weeks of 2014:Q2. Question 1 asks for the change in sales between 2013:Q4 and 2014:Q1. This is the most recent sales growth realization that the firm has experienced. Question 2 then asks for the firm's outlook over the current quarter 2014:Q2, as compared to the last quarter 2014:Q1. This is the next growth rate realization that the firm expects.

Our quantitative measure of subjective uncertainty is the *span* between the best and worst case scenarios for sales growth that firms provide in response to question 2.a. A firm's *forecast error* is the difference between its actual sales growth in the current quarter and its expected growth rate at the beginning of that quarter, that is, its answer to part 2.b. At the beginning of every quarter, firms cannot perfectly predict the flow of sales over the entire quarter; the forecast errors thus captures the mistakes they make.

Sample construction

We describe the construction of our baseline sample, including all the data cleaning steps, in detail in Appendix 1.C. Briefly, in a first step, we focus on firms that have at least five sensible firm-wave observations of the previous-quarter sales growth rate (question 1). Text comments provided by firms are useful here both to assess outliers and to drop firms unwilling or unable to provide quarterly forecasts. The five-observations threshold allows us to compute meaningful time series means and volatilities of sales growth rates for firms in this sample. We use both as important firm-level control variables in our analyses.

Our baseline sample needs to have also consistent and realistic answers to the second question in the survey about the sales growth scenarios and consists, in the end, of 400 firms and 2762 firm-wave observations from 14 quarters. We know each firm's sector at the two-digit manufacturing level and form 14 supersectors for which we have a sufficiently large number of observations. Table 1.D.1 in Appendix 1.D presents the distribution of firms across sectors.

Survey questions that ask about realized outcomes (such as production) explicitly ask firms to ignore seasonal fluctuations. Consistent with this, we observe only negligible seasonal effects in our data. Indeed, at the sectoral level, we can compare the sales growth rates measured in our survey – and thus deseasonalized by the individual firms – with a seasonally adjusted time series of manufacturing sales growth rates measured by the Federal Statistical Office, Destatis, through an unrelated survey. The time series correlation between the Destatis series and our series is 0.76. We thus treat the variables below as seasonally adjusted at the individual firm level.

1.2.3 Span as a Measure of Subjective Uncertainty

The premise behind our survey module is that when firms worry more about the future, they contemplate positive and negative scenarios that are further apart, and hence exhibit higher span. Movements in span can in principle reflect changes in either beliefs or attitude towards uncertainty. On the one hand, a firm might worry more about the future because it has less information and hence perceives a lot of uncertainty. It might then modify its planning process to consider scenarios that are further away from the baseline. Alternatively, the firm may worry more in the sense that it becomes more cautious in its approach to planning under uncertainty. This might lead it to alter scenarios even if beliefs are the same.

The metasurvey results provide further evidence on how firms choose the reported scenarios. One question asks firms whether they view scenarios as "plausible" or "possible but exceptional". The third panel of Table 1.1 shows the results: an overwhelming majority of firms, 76%, respond "plausible", regardless of size class. In light of this finding, we would expect that realized growth often falls outside the interval bounded by the best and worst cases. This is indeed the case in our data. In a pooled sample of firm-quarter observations, the share of instances where growth is outside the bounds is 48% for firms that consider scenarios "plausible" and still 40% for those that consider them "possible but exceptional". We conclude that firms generally like to think about scenarios that are quite likely.[11]

The metasurvey also confirms that survey answers reflect both information and attitude towards uncertainty to a significant extent. Indeed, we ask firms to rate, on a four point scale, the importance of various determinants for their choice of scenarios. The results are summarized in Table 1.2. They show that the most relevant factors mentioned by firms are risk attitude, recent experience of own sales growth and news about the future unrelated to past sales growth. In contrast, the typical firm does not attribute an important role to sales growth more than two years in the past as well as the observation of competitors. Again these results vary little across size classes.

These findings clarify that span is a measure of "worry" about future uncertainty that guides firm planning, as opposed to, say, only a measure of perceived risk. Of course, there are conditions under which worry and perceived risk are the same. To illustrate, consider a firm with decision makers who think about risk and reward in terms of mean and variance, and maximize a textbook objective that is linear in both moments,

[11] This finding suggests that it is generally difficult to elicit support bounds and hence probability distributions in a survey when there are no prespecified bounds.

Table 1.2: Meta Survey 2018 answers on determinants of scenarios

	Very important	Important	"Very important" or "Important"		
			Tiny & Small	Medium	Large
Sales changes last 1 to 2 years	0.21	0.37	0.58	0.71	0.40
Sales changes more than 2 years ago	0.02	0.09	0.09	0.16	0.06
Considerations independent of past sales changes	0.41	0.49	0.85	0.93	0.91
Our risk attitude	0.19	0.57	0.78	0.86	0.60
Sales change we observe with competitors	0.04	0.26	0.29	0.30	0.32

Notes: The numbers are from the fall 2018 meta survey on a sample of 191 firms. Respondents are asked to assess the importance of several aspects for determining scenarios for sales growth in the best and worst case. Columns 1 and 2 report the overall share, while columns 3 to 5 show the share by three size groups. In line with the definition by the German Statistical Office, firms are “tiny” if the have less than 10 employees, “small” if the number of employees is between 10 and 50, “medium” if the number of employees is between 50 and 250, and “large” if the number of employees exceeds 250. We present the shares of firms that consider the determinants, respectively, as “very important” and “important” for the choice of scenarios. The other answer options were “less important” and “not important.” Column 3 to 5 show the sum of the shares answering with “very important” or “important” by size group.

with a fixed coefficient on variance capturing risk aversion. For such a firm, changes in worry about the future that are relevant for actions come only from changes in conditional variance. We would thus expect span to reflect the dispersion of the firm’s subjective conditional distribution.

More generally, our focus on "worry" means that our measure reflects changes in perceived risk only to the extent that they are actually relevant to the firm’s planning process. For example, an increase in risk will have a smaller effect on firm planning if the firm’s objective does not strongly respond to risk. We would thus expect a smaller change in span. In fact, it is plausible to have two firms that face the same change in risk, but see span move more for one of them because it plans more cautiously. Put differently, span is best viewed as the *outcome* of a change in risk (or risk attitude): it captures how the planning process of the firm changes.

How can span be used to quantify models of the firm? In economic models, "worry" about uncertainty is usually captured by a certainty equivalent function. For example, in a standard model of firm dynamics, we can use the value function of the firm together with its conditional distribution of shocks to ask how much a firm would be willing to pay to remove the uncertainty. The answer would generally depend not only on the firm’s perceived risk, but also on the curvature of the objective function. The latter might be driven by various features of the firm’s environment such as technology, managerial risk aversion, or financial frictions. Since planning for scenarios takes these features into account, we think of span as a proxy for worry that is measured using the certainty equivalent approach.

An additional advantage of our focus on "worry" as opposed to risk is that positive and negative scenarios – and hence span – are meaningful numbers for a firm whether or not it routinely reasons in terms of probabilities. As we have seen in Section 1.2.1, more than half of firms consider statistical analysis as unimportant for answering our survey. At the same time, 80% of firms routinely rely on *some* kind of quantitative analysis, in particular scenario analysis. Our question is designed to make sense to all firms and encourage them to use data from routine quantitative analysis. Firms that develop probabilistic forecasts can provide quantiles from their subjective distribution. Firms that only assess the effect of scenarios without assigning probabilities can report what those scenarios are.[12]

1.2.4 Properties of Subjective Uncertainty

In this section, we present stylized facts on span and its relationship to volatility. Detailed tables of summary statistics for answers to the uncertainty module questions are provided in Appendix 1.E.

Sales growth is hard to predict

Realized firm sales growth has a standard deviation close to 15 percentage points and an interquartile (IQ) range from -5% to 10%. Relative to this variation, the distribution of forecasts is compressed, with an IQ range from zero to 5%. The variance of forecasts is about half that of the realizations. Forecasts display little bias on average: the average forecast is only slightly higher than the average realization. For an average firm, the standard deviation of forecast errors is 10.2pp, similar in magnitude to volatility (standard deviation) of its sales growth of 11.4pp. Together, these moments indicate that predicting sales growth is difficult: unpredictable variation is close to total variation.

One might suspect that firms provide forecasts in a mechanical way by simply using past growth or some constant baseline growth rate. In our data, both hypotheses are false. Indeed, the difference between a firm's forecast and its last realization of growth

[12] The same connection to economic models applies for firms that do not think in terms of probabilities. For example, firms might maximize an objective function that exhibits a concern for robustness or aversion for Knightian uncertainty. It is still possible to compute a certainty equivalent and use data on span to calibrate the model.

has a standard deviation of 17.2 percentage points, larger than that of the forecast itself. At the same time, the difference between a firm's forecast and its firm level mean growth rate has a standard deviation of 10.8 percentage points. The results show that these simple models generate growth predictions that deviate substantially from firms' actual forecasts. We conclude that firms' forecasts are nontrivial functions of past growth.

Best and worst case scenarios and the magnitude of subjective uncertainty

Firms' best and worst case scenarios bracket forecasts almost symmetrically. The average worst and best case bounds are -4.8% and 7.4%, respectively. The midpoint between these bounds is 1.3% and hence less than one percentage point below the average forecast of 2.2%. Individual bounds have slightly higher standard deviations and wider IQ ranges than forecasts. A key difference between the variables is that the distribution of the lower (upper) bound is negatively (positively) skewed.

Our measure of subjective uncertainty is similar in magnitude to firm level unconditional volatility. Indeed, the mean span in the pooled sample is 12.1 percentage points, while the cross sectional mean of firms' time series standard deviation of growth rates is 11.4%. Since growth is hard to predict, the span reported by the average firm is also similar in magnitude to the typical absolute forecast error experienced by a firm, 9.4% in the pooled sample.

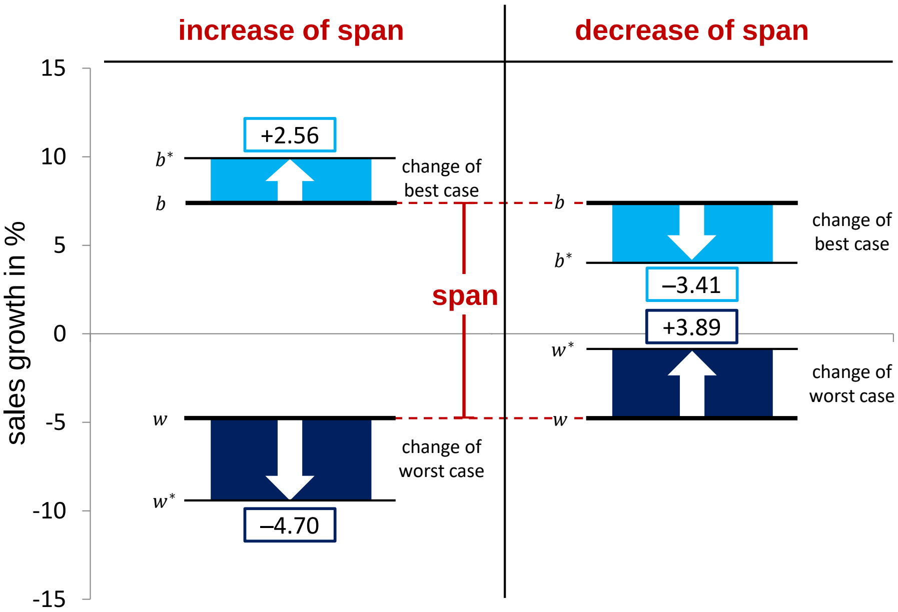
Subjective uncertainty varies in cross section

To assess the variation of subjective uncertainty in the cross section, we compute the average span for each firm. The cross sectional standard deviation of average span is 7.4%. It is similar in magnitude to the cross sectional standard deviation of the average absolute forecast error of 9.5%. Firms thus differ substantially in both the size of the typical shock they experience and in the way their planning deals with perceived uncertainty.

Subjective uncertainty varies in time series at firm level

Our data also show substantial time variation in subjective uncertainty at the firm level. The sample standard deviation of span for the average firm in Figure 1.E.2 is 5.9 percentage points and hence more than half of the standard deviation of span in the pooled sample. Time series variation in subjective uncertainty is also large compared to other changes in firms' beliefs. For example, the cross sectional mean of firms' time series standard deviation of forecasts is 7.2 percentage points and numbers for best and

Figure 1.2: Changes in subjective uncertainty



Notes: The figure illustrates how, on average, changes in the best and worst case scenarios generate increases and decreases of subjective uncertainty (span). The plot shows the pooled averages of span as well as the pooled averages of the best and worst case sales growth rates, which are denoted by b and w, respectively. b^* and w^* are the best and worst case scenarios after the average changes of span.

worst scenarios are only slightly higher. A firm's span usually changes together with its forecast: only 13% of changes in span are not accompanied by a forecast revision.

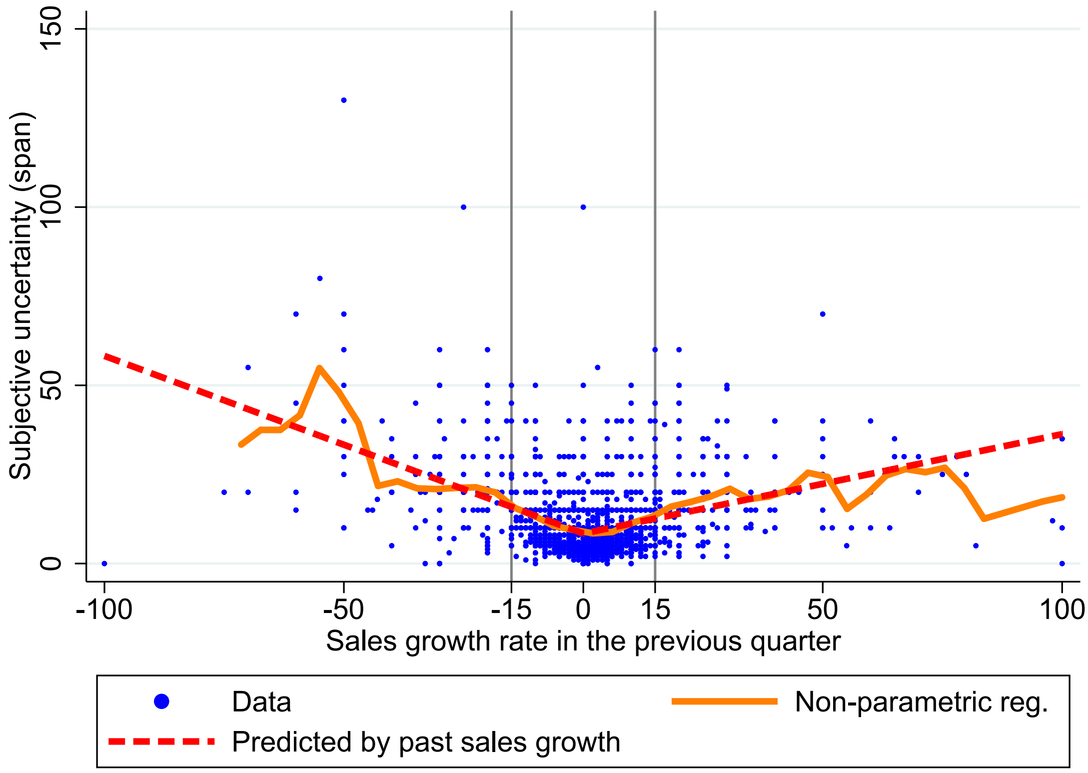
What do *changes* in uncertainty look like? On average, they consist of moves in both the best and worst case scenarios. In particular, for all instances where a firm increases its span from one quarter to the next, the mean change in the worst case scenario is -4.7% whereas the mean change in the best case scenario is $+2.6\%$, see Figure 1.2. In other words, the average increase in uncertainty thus consists of an outward expansion of span that is slightly asymmetric. The average decrease in span is a symmetric downward compression: conditional on a decrease in span, the worst case increases by 3.8% and the best case decreases by 3.4%.

The variation of subjective uncertainty in both time series and cross section is overwhelmingly firm-specific. Indeed, the R-squared of a regression of span on time fixed effects is 0.006, on time and industry fixed effects 0.030, and on time-industry fixed effects it is merely 0.084.[13] This fact does not imply that we cannot uncover patterns in the variation of span, as we will see below. It simply means that the cross sectional

[13] The variation in firms' forecast errors and absolute forecast errors is also overwhelmingly firm-specific. For absolute forecast errors, a regression on time fixed effects yields a R-squared of 0.014, a regression on time and industry effects a R-squared of 0.033, and a regression on time-industry fixed effects a R-squared of 0.12.

patterns are not driven by the industry, but rather by differences in firm perceptions within industries. Similarly, the time series patterns are driven by individual firm experiences as opposed to, say, the state of the business cycle.

Figure 1.3: Uncertainty and past sales growth



Notes: Every dot represents a firm-time observation. The solid line is the prediction from a non-parametric kernel regression. The dashed line depicts the predicted values from a piecewise linear regression of subjective uncertainty on past sales growth, with a break at zero. The thin vertical lines mark the interdecile range that extends from −15% to 15%, see Tab. 1.E.1.

1.3 Uncertainty and Change

How does firm's subjective uncertainty relate to their experience? In this section, we first present a key stylized fact on subjective uncertainty and change. We then lay out a simple organizing framework that guides our subsequent analysis.

1.3.1 Uncertainty and Past Growth: An Asymmetric V

Figure 1.3 displays a scatter plot of responses, with span at the beginning of quarter t along the vertical axis and sales growth realized between quarters $t-2$ and $t-1$

along the horizontal axis. The vertical gray lines indicate the interdecile range which reaches from -15% to $+15\%$ as reported in Table 1.E.1.

Firms that have experienced larger changes are more uncertain. In particular, the relationship between subjective uncertainty and past sales growth looks like the letter V with a minimum at zero. This is illustrated in the figure by two lines. The solid line is a nonparametric regression line.[14] The dashed line is from a simple piecewise linear regression with a breakpoint at zero.[15] The two lines are very similar, and they virtually coincide in the relevant range where most observations are located.

Firms perceive higher uncertainty after negative change than after positive change. Indeed, the slope of the left hand branch of the letter V is about twice as large in absolute value as the slope of the right hand branch. After a one percentage point lower negative sales growth, next quarter's span is half a percentage point wider. In contrast, after one percentage point higher positive sales growth, span is wider by slightly more then one quarter of a percentage point wider. The regression coefficients are reported in column (2) of Table 1.5, discussed further below.

The V-shaped regression line relates uncertainty to change; it stands in contrast to the simple linear relationship between uncertainty and growth often emphasized in the literature. At the same time, asymmetry implies that uncertainty and growth are in fact negatively correlated. Indeed, a linear regression returns a small but significantly negative coefficient of -.06, shown below in column (1) of Table 1.5. However, ignoring the V-shape drastically lowers explanatory power of past sales growth rate from 19% for a piecewise linear regression to 1% for the simple linear regression.

1.3.2 Uncertainty and Change: An Organizing Framework

Our organizing framework relates a firm's subjective uncertainty to the distribution of growth measured by an econometrician. We use it in later sections to guide our detailed discussion of uncertainty and change in both the cross section and the time series. For simplicity, we assume that firms have probabilistic beliefs. As will become

[14] We use a kernel-weighted local polynomial regression with a plugin estimator of the asymptotically optimal constant bandwidth as described in Fan and Gijbels (1996). We report the results of a polynomial of degree zero and Epanechnikov kernel. However, the shape of the regression line is robust – except at the outer margins – to choosing a higher order polynomial or different kernels.

[15] We have compared the in-sample fit of a piecewise linear regression model with breakpoint at zero with a simple quadratic model. Both Akaike and Bayesian information criterion favor the piecewise linear model.

clear, this feature is not essential for the points we make here, but it allows us to express those points in simple familiar notation.

Let g^i_{t+1} denote firm i's sales growth from quarter t to quarter $t+1$, that is, the growth rate that firm i forms beliefs about when it answers our survey questions at the beginning of quarter $t+1$. Firm i's information set at that point in time includes g^i_t, the last observed growth rate from quarter $t-1$ to t. It may also include other signals that represent news in quarter t, which we collect in a vector z^i_t. We then use the vector s^i_t to represent all information from past growth rates or other signals that is relevant for forecasting the future dynamics of growth.

We represent firm i's belief about its sales growth by the state space system

$$g^i_{t+1} = f\left(s^i_t, x^i\right) + \sigma\left(s^i_t, x^i\right)\varepsilon^i_{t+1} \tag{1.1}$$
$$s^i_t = S\left(s^i_{t-1}, g^i_t, z^i_t; x^i\right) \tag{1.2}$$

where x^i is a vector of fixed firm characteristics and ε^i_t is an error that has mean zero and variance one under the firms' subjective belief. The observation equation allows firm i's forecast $f(s^i_t, x^i)$ to depend on the state as well as its fixed characteristics. The state is updated every period to incorporate new information in g^i_t and z^i_t according to the function S.

When firm i answers our survey questions at the beginning of quarter $t+1$, it provides its forecast $f(s^i_t, x^i)$ as well as best and worst case scenarios. We also observe the subsequent realization g^i_{t+1} and hence the firm's subjective forecast error. We further identify span, the difference between firm i's best and worst case scenarios, with firm i's subjective conditional volatility $\sigma(s^i_t, x^i)$. This connection is exact if firm i reports quantiles as scenarios and appropriate distributional assumptions are in place. More generally, we expect firm i's answer to the survey question to reflect some measure of dispersion in its forecast error, so σ serves as a concrete stand-in.

Examples

The state space system (1.1)-(1.2) nests many models used to describe firms' subjective uncertainty in economic models. As a simple example, consider the case of iid growth together with an orthogonal uncertainty shock:

$$g^i_{t+1} = f + \sigma^i_t \varepsilon^i_{t+1} \tag{1.3}$$
$$\sigma^i_t = S\left(\sigma^i_{t-1}, z^i_t\right) \tag{1.4}$$

Here the only relevant state is stochastic volatility σ_t^i. Rational expectations models with uncertainty shocks often assume that σ_t^i is correlated across firms and high in recessions, which helps generate observed dispersion in firm growth rates in bad times.

The system (1.1)-(1.2) also nests many popular learning rules. Examples include Bayesian models where firms track some latent state such as a regime, or constant gains learning where firms recursively estimate parameters of the one step ahead predictive distribution while downweighting past observations. The common denominator of all these setups is that the state vector contains statistics of the empirical distribution that are relevant for predicting the future dynamics of growth. A natural property in many settings is that high growth g_t^i increases the forecast f and that a large absolute value of the forecast error increases subjective uncertainty σ.

Comparing beliefs and the true data generating process

We would like to distinguish firms' subjective uncertainty from actual volatility, as reflected in the size of innovations measured by an econometrician. We thus consider a change of measure from the firm's belief to the "econometrician's belief", that is, the probability measure that characterizes the true data generating process. We assume that under the econometrician's belief the distribution of growth rates has the alternative representation

$$\begin{aligned} g_{t+1}^i &= f\left(s_t^i, x^i\right) + b^i\left(s_t^i, x^i\right) + \hat{\sigma}\left(s_t, x^i\right)\hat{\varepsilon}_{t+1}^i && (1.5) \\ s_t^i &= \hat{S}\left(s_{t-1}^i, g_t^i, z_t^i\right) && (1.6) \end{aligned}$$

where again the error has mean zero and variance one, now under the econometrician's belief.

The new observation equation allows for two key differences between firms' belief and the true data generating process. First, firms might have biased forecasts, represented by the function b. Second, the size of the typical innovation $\hat{\sigma}$ might be different from firms' subjective uncertainty captured by σ. Both differences may vary either in the cross section with firms' fixed characteristics x^i or over time with the information set captured by s_t^i. In the special case of rational expectations, there is no bias ($b = 0$) and subjective uncertainty mirrors actual volatility, that is, $\sigma = \hat{\sigma}$.

1.4 Uncertainty and Change in the Cross Section

In this section, we ask what type of firms perceive more subjective uncertainty *on average*. We thus compute, for each firm, its average span, that is, the time series mean of all observations of span for the firm. We then regress average span on a number of firm level characteristics. In terms of the framework of Section 1.3.2, we thus characterize the dependence of subjective uncertainty σ on fixed characteristics x^i, assuming that time averaging removes the effects of information s_t^i.

1.4.1 Change in Firms' Environment

We define two variables that measure the medium term dynamics in a firm's environment, based on its realized sales growth rates (that is, answers to part 1). We refer to a firm's sample average sales growth as its *trend*.[16] Moreover, the *turbulence* experienced by a firm is measured by the sample standard deviation of its sales growth rates. We emphasize that turbulence differs from span for two reasons: First, it is purely statistical as it is based on realized growth rates. Second, it is an unconditional average over three years, whereas span measures conditional uncertainty one quarter ahead.

To tractably account for nonlinear effects of firm characteristics on average span, we code the firm characteristics as dummies. In particular, we use our turbulence dummies that indicate quartiles of the distribution of firm level standard deviations in Table 1.E.2, with the lowest quartile as the baseline. We proceed similarly for trend, However, since the middle two quartiles for trend turn out to be very similar, we introduce dummies only for a low trend (bottom 25%) as well as a high trend (top 25%), treating the middle group as the baseline.

Finally, we divide firms into four size categories, with size measured as average employment over our sample. Here we follow the German Statistical Office in their definition of tiny, small, medium sized, and large firms; lower bounds for the latter three

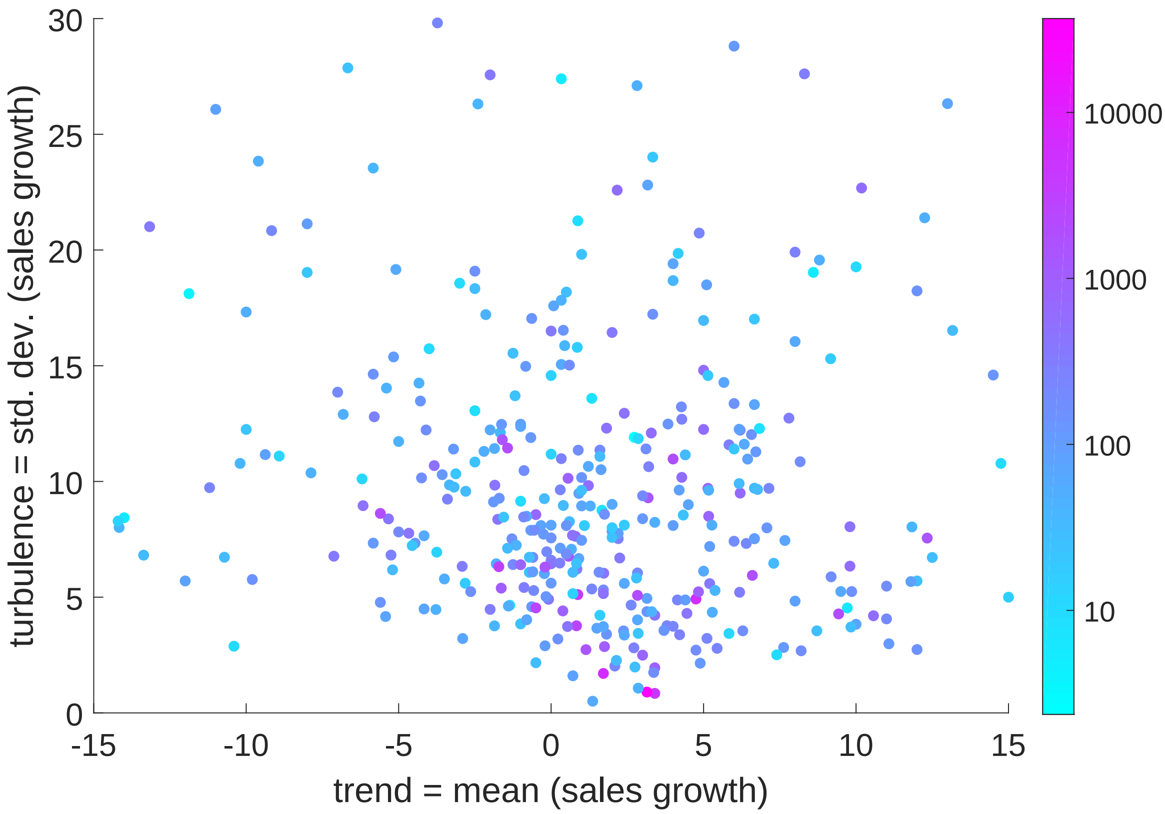
[16] We verify with the help of the general ifo Business Survey that growing firms tended to have good business situations for several years before the start of our sample in 2013:Q2; and analogously for shrinking firms and bad business situations. Specifically, we compute the firms' average subjective state of business assessments, elicited on a scale between 0 and 100, from January 2010 to July 2016 (monthly frequency). 52% of the firms on a good sales growth trend were, on average since 2010, also in the best quartile of the state of business distribution across firms. Of the firms with a normal sales growth trend, 55% were in the second or third quartile of the state of business distribution across firms, and of the firms in the lowest quartile, 39% were also in the lowest quartile of the state of business distribution across firms.

groups are at 10, 50, and 250 employees, respectively. We work with three dummies, with tiny firms as the baseline.

Figure 1.4 provides a scatter plot of trend and turbulence, defined above as the firm level mean and standard deviation of sales growth, respectively. Every dot represents a firm, and the color of the dot indicates firm size, as measured by the number of employees. Size increases from light blue to pink according to the color bar provided on the right hand side of the figure.

The main takeaway from Figure 1.4 is that while trend and turbulence vary substantially – as Table 1.E.2 also shows –, they are not particularly correlated. Firms that grow or shrink along strong trends need not typically experience large shocks and vice versa. Moreover, the correlation of either environment variable with size is also quite weak. While the very largest firms (identified by bright pink dots) do tend to cluster at the bottom center where trend is small and turbulence is low, we observe firms of all sizes spread out over the plane.

Figure 1.4: Trend and turbulence



Notes: Every dot represents a firm identified by its trend (firm level mean sales growth) and turbulence (standard deviation of mean sales growth). Color indicates number of employees according to color bar on right hand side.

1.4.2 Subjective Uncertainty, Size, Trend, and Turbulence

Table 1.3 presents regression results. The first three columns ask how much can be explained by each fixed characteristic – size, trend and turbulence – separately. All three characteristics show a statistically and economically strong association with span. Column (1) says that larger firms perceive less uncertainty. Average span in the entire population of firms is about 12 percentage points, and it falls monotonically from 18 percentage points for very small firms (the omitted category) to 10 percentage points for large firms.

Columns (2) and (3) show that cross sectional variation in trend and turbulence – each by itself – is enough to induce a V-shaped relationship between growth and uncertainty, as observed in the pooled scatter plot. On the one hand, trend and span are directly related by an asymmetric V: quickly shrinking or growing firms report higher average spans than firms with normal growth, by 2 and 6 percentage points, respectively. On the other hand, more turbulent firms also report monotonically higher spans. Since more turbulent firms' growth rate realizations fall more into the tails, this effect also generates a V pattern.

Each of the three firm characteristics has independent effects on the average subjective uncertainty of firms. This is established in column (4) where we consider all three in the same regression. The positive turbulence gradient is qualitatively and quantitatively unchanged compared to the results in column (3). For trend, the interaction with other characteristics is more subtle. In particular, once size and turbulence are controlled for, growing firms no longer perceive higher uncertainty. At the same time, the negative branch of the V remains large and statistically significant.

While trend and turbulence are correlated with size, controlling for them does not remove an independent role for size in explaining subjective uncertainty. Indeed, comparing columns (1) and (4), the negative size gradient is quantitatively reduced, but remains in place qualitatively. Column (5) further shows that our three firm characteristics are not simply reflective of industry characteristics: including industry dummies neither changes significantly the R-squared of compared to column (4) nor the coefficient estimates.

Table 1.3: Subjective uncertainty and forecast errors by firm characteristics

Dependent variable:	(1) avg. span	(2) avg. span	(3) avg. span	(4) avg. span	(5) avg. span	(6) avg. abs. FE	(7) avg. FE
Dummy small firms	-3.267*			-1.610	-1.936	1.217	4.147
	(1.923)			(1.655)	(1.729)	(2.255)	(2.800)
Dummy medium sized firms	-6.402***			-3.711**	-4.308***	-0.165	1.557
	(1.794)			(1.550)	(1.623)	(2.067)	(2.508)
Dummy large firms	-8.834***			-5.051***	-5.705***	-0.568	3.036
	(1.827)			(1.603)	(1.716)	(2.056)	(2.486)
Dummy 'bad' sales growth trend		5.940***		3.233***	3.209***	2.663***	-5.322***
		(0.936)		(0.821)	(0.850)	(0.934)	(1.221)
Dummy 'good' sales growth trend		2.177***		0.444	0.190	2.489**	5.358***
		(0.800)		(0.730)	(0.739)	(1.126)	(1.364)
Dummy medium low turbulence			2.287***	1.731***	1.751***	2.816***	-0.0552
			(0.623)	(0.613)	(0.664)	(0.515)	(0.733)
Dummy medium high turbulence			6.028***	5.052***	4.985***	5.259***	0.0525
			(0.725)	(0.701)	(0.723)	(0.561)	(0.891)
Dummy high turbulence			11.28***	9.625***	9.216***	13.33***	0.0624
			(0.892)	(0.865)	(0.898)	(1.393)	(1.640)
Constant	18.16***	10.32***	7.456***	10.61***	10.96***	2.734	-2.741
	(1.731)	(0.456)	(0.366)	(1.567)	(1.790)	(2.082)	(2.498)
Sector dummies					YES		
No. of observations	400	400	400	400	400	389	389
No. of firms	400	400	400	400	400	389	389
No. of parameters (excl. intercept)	3	2	3	8	21	8	8
R-squared	0.10	0.11	0.34	0.41	0.43	0.35	0.14

Notes: Results from pooled OLS regressions. avg. span denotes the time-series average of firm-level span, avg. abs. FE denotes the time-series average of the firm-level absolute forecast error, and aver. FE denotes the time-series average of the firm-level forecast error. Size dummies are defined based on the firm-level average number of employees. Standard errors in parentheses, clustered by firm; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

It is also interesting to consider firm age as a cross-sectional determinant of average subjective uncertainty. While there is no age variable available in ifo's Business Tendency Survey, in September 2018 a special survey question asked firms for their founding year. 274 of the firms in our baseline sample responded to this question. For those, we can construct an age variable. To account for non-linear effects, we construct quartile dummies for firm age. We regress the average span on these age dummies and additionally include size, trend, and turbulence dummies. None of the coefficients on the age dummies in this regression is statistically significant to the 10%-level. We conclude that firm age cannot explain a firms' average subjective uncertainty.

1.4.3 Subjective Uncertainty, Volatility, and Bias in the Cross Section

How does firms' perceived uncertainty relate to the size of the fluctuations they experience? Column (6) of Table 1.3 reports a regression of firms' average volatility on fixed characteristics. Since span reflects perceived uncertainty *conditional* on information at the beginning of the quarter, column (7) adds an analogous regression for the average absolute value of the firm's subjective forecast error, a measure of the size of innovations experienced by the firm. The results in the two columns are quite similar.

Along all three cross sectional dimensions we consider, subjective uncertainty is significantly different from the size of shocks experienced by the typical firm. First, for both volatility and the absolute forecast error, there is no independent effect of size once we control for trend and turbulence. It is true that unconditionally larger firms experience smaller shocks. However, this relationship is entirely explained by their trend and turbulence. We conclude that the additional effect of size on span is a subjective phenomenon: large firms' perceive lower uncertainty even if they face the same size of shocks as smaller firms.

A second special feature of subjective uncertainty is its asymmetric dependence on trend. While it is true that growing and shrinking firms also experience larger shocks, this effect is symmetric. For the same shocks, shrinking firms thus perceive higher subjective uncertainty. A final property concerns the turbulence gradient. While more turbulent firms – who experience larger shocks by construction – also perceive higher uncertainty, they are relatively much less uncertain than low turbulence firms.

As discussed in Section 1.3.2, forecast errors experienced by firms may in part reflect systematic bias in firms' forecasts. Column (7) of Table 1.3 shows a regression of the mean forecast error on characteristics. For the size and turbulence categories, the coefficients on the dummies are not statistically significant. Consistent with this result, group means (not reported) are zero if firms are sorted into size or turbulence categories.

At the same time, there is strong evidence that firms on trends make biased forecasts. In particular, growing firms make large positive forecast errors, defined above as realized growth less forecast. In other words, growing firms are regularly positively surprised; their forecasts are biased towards zero. Analogously, shrinking firms make large negative forecast errors: again the forecast is biased towards zero – firms do not sufficiently anticipate the trend they are on.

Table 1.4: Volatility of subjective uncertainty by firm characteristics

	(1)	(2)	(3)	(4)
Dependent variable:	std. span	std. span	std. span	std. span
Dummy small firms	-3.053**			-2.084*
	(1.485)			(1.254)
Dummy medium sized firms	-4.252***			-2.655**
	(1.470)			(1.292)
Dummy large firms	-5.094***			-2.798**
	(1.481)			(1.294)
Dummy ’bad’ sales growth trend		3.603***		2.164***
		(0.802)		(0.684)
Dummy ’good’ sales growth trend		1.672***		0.771*
		(0.475)		(0.450)
Dummy medium low turbulence			1.254***	1.000**
			(0.384)	(0.387)
Dummy medium high turbulence			2.907***	2.369***
			(0.321)	(0.353)
Dummy high turbulence			6.364***	5.463***
			(0.797)	(0.717)
Constant	9.767***	4.543***	3.237***	5.337***
	(1.415)	(0.208)	(0.184)	(1.251)
No. of observations	397	397	397	397
No. of firms	397	397	397	397
No. of parameters (excl. intercept)	3	2	3	8
R-squared	0.052	0.086	0.22	0.27

Notes: Results from pooled OLS regressions. std. span denotes the time-series standard deviation of firm-level span. Standard errors in parentheses, clustered by firm; * p < 0.10, ** p < 0.05, *** p < 0.01. Size dummies are defined based on the firm-level average number of employees.

1.4.4 Heteroscedasticity and Firm Charateristics

In the previous section, we have shown that there is substantial heteroscedasticity in firms’ subjective uncertainty along observable firm characteristics: size, trend growth, and turbulence, the latter two being measures of the intensity of change in the firm's environment. We have also shown that heteroscedasticity in firms' subjective uncertainty is substantially different from that in conditional and unconditional volatility. In this section, we argue that subjective heteroscedasticity itself is related to firms' characteristics in very similar ways as subjective uncertainty.

For example, column (1) of Table 1.4 shows that smaller firms are more different in their subjective uncertainty. Column (2) finds that firms on a substantial positive or negative trend have higher dispersion in average subjective uncertainty; and column (3) shows a positive correlation between sample volatility and dispersion in subjective uncertainty: firms in the most volatile environments are also the most different in terms of their average perceived uncertainty. These results show that the structure of uncertainty in the cross section of firms is at least somewhat predictable but also complex, which requires a substantial amount of heterogeneity to be modeled in any nonlinear model environment.

1.5 Uncertainty and Change Over Time

We have seen in the previous section that the V-shaped relationship between growth and uncertainty in Figure 1.3 in part reflects fixed differences between firms. We now turn to time series variation: we ask how much of a V remains once we control for fixed characteristics. In terms of the organizing framework of Section 1.3.2, we ask whether variation of span σ with firms' information s_t^i also contributes to the V-shape, via the correlation of s_t^i with past growth.

Formally, let $\Delta y_{i,t-1}$ denote firm i's sales growth rate between quarters $t-2$ and $t-1$. All our specifications take the form

$$span_{it} = \beta^- \Delta y^-_{i,t-1} + \beta^+ \Delta y^+_{i,t-1} + \gamma' x_i + \epsilon_{it},$$

where $\Delta y^-_{i,t-1} = \Delta y_{i,t-1} I(\Delta y_{i,t-1}<0)$, $\Delta y^+_{i,t-1} = \Delta y_{i,t-1} I(\Delta y_{i,t-1} \geq 0)$, $I(\cdot)$ is the indicator function, and x_i is a vector of fixed firm characteristics that do not depend on time.

We include the three characteristics studied in the previous section: trend, turbulence and size. Trend and turbulence are again coded as dummies. As the unit of observation is now a firm quarter pair, we measure the size of the firm as the number of employees at the end of the previous calendar year. We then form three size dummies: small firms have 10-50 employees, medium sized firms 51-250 employees and large firms more than 250 employees. The baseline "tiny" firm has fewer than 10 employees. While size therefore does vary over time, change is so slow such that the size dummies are essentially time-invariant. We observe only 56 jumps from one size category to another in our sample.

1.5.1 Time Variation in Subjective Uncertainty and Growth

Table 1.5 reports regression results. As a benchmark, we start in columns (1) and (2) with a simple linear regression and a piecewise linear regression with a break at zero, respectively. The two columns provide formal counterparts to the scatter plot Figure 1.3. The next four columns augment the piecewise linear specification with dummies for fixed characteristics, first adding size, trend and turbulence separately, and then in column (6) adding all characteristics together.

The main result from Table 1.5 is that a strongly significant asymmetric V remains even if we control for fixed characteristics. Indeed, the coefficients on both negative and positive past sales growth are statistically significant in all specifications.[17] Column (6) says that, holding fixed all characteristics, after one percent lower negative sales growth, next quarter's span is 30 basis points wider. Similarly, a one percent higher positive sales growth is followed by a 18 bp wider span. To put these numbers in perspective, note that the volatility of sales growth for the average firm is about 11 percentage points, whereas the volatility of span for the average firm is about 6. Responses to past growth thus account for a considerable part of time variation in subjective uncertainty.

The impact of firm characteristics is also significant. First, introducing firm characteristics dummies improves the fit of the regression: for example, the R-squared improves from 0.19 in column (2) to 0.29 in column (6). Coefficients on the dummies reproduce the cross sectional effects discussed in the previous section. For example, firms with more than 250 employees are more than 6 percentage points less uncertain on average than very small firms. Firms that experience more than median turbulence are at least 4.5 percentage points more uncertain than those with low turbulence. The impact of trend is asymmetric: firms on a bad trend are more than 2 percentage points more uncertain than those on a normal trend, whereas a good trend has no significant effect on span.

[17] Appendix 1.G shows that this result is robust to re-estimating the regression using two alternative sample definitions.

Table 1.5: Subjective uncertainty and past sales growth

Dependent variable: span between best and worst case sales growth rate for quarter t	(1) POLS	(2) POLS	(3) POLS	(4) POLS	(5) POLS	(6) POLS	(7) FE	(8) POLS
Sales growth rate in quarter $t-1$	-0.0598**							
	(0.0259)							
Negative sales growth rate in quarter $t-1$		-0.498***	-0.470***	-0.436***	-0.351***	-0.306***	-0.272***	-0.304***
		(0.0612)	(0.0602)	(0.0626)	(0.0661)	(0.0675)	(0.0786)	(0.0686)
Positive sales growth rate in quarter $t-1$		0.279***	0.266***	0.280***	0.166***	0.180***	0.159***	0.173***
		(0.0329)	(0.0317)	(0.0327)	(0.0335)	(0.0314)	(0.0319)	(0.0303)
Dummy small firms			-4.480*			-3.959*		-3.508*
			(2.560)			(2.178)		(1.897)
Dummy medium sized firms			-6.677***			-5.452**		-5.157***
			(2.516)			(2.141)		(1.972)
Dummy large firms			-7.858***			-6.295***		-5.970***
			(2.570)			(2.170)		(2.014)
Dummy 'bad' sales growth trend				3.711***		2.248***		2.300***
				(0.951)		(0.856)		(0.858)
Dummy 'good' sales growth trend				0.410		-0.434		-0.618
				(0.658)		(0.645)		(0.667)
Dummy medium low turbulence					1.699***	1.388**		1.340**
					(0.578)	(0.591)		(0.649)
Dummy medium high turbulence					5.157***	4.560***		4.572***
					(0.752)	(0.764)		(0.772)
Dummy high turbulence					7.702***	6.748***		6.525***
					(1.035)	(0.969)		(0.979)
Intercept	12.22***	8.428***	14.76***	7.695***	6.206***	11.37***	10.06***	9.774***
	(0.392)	(0.435)	(2.532)	(0.435)	(0.425)	(2.154)	(0.480)	(3.014)
Time-sector dummies								YES
No. of observations	2762	2762	2762	2762	2762	2762	2762	2762
No. of firms	400	400	400	400	400	400	400	400
No. of parameters (excl. intercept)	1	2	5	4	5	10	401	199
R-squared	0.0079	0.19	0.22	0.21	0.26	0.29	0.57	0.34

Notes: Results from pooled OLS (POLS) and fixed effect (FE) regressions. Piecewise linear regressions of span on past sales growth with a break at zero in columns 2 to 8, controlling for fixed firm characteristics. Standard errors in parentheses, clustered by firm. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

It is natural to conjecture that fixed characteristics other than size, trend and turbulence matter for subjective uncertainty. We thus rerun the regression in column (7) with firm fixed effects. As expected, we find a large increase in R^2. Remarkably, however, there is virtually no change in the coefficients on past growth. We can thus conclude that size, trend and turbulence dummies exhaustively control for the impact of firm characteristics on the uncertainty-growth relationship.

In column (8), we include time-sector dummies. This neither alters our coefficient estimates nor markedly improves the fit of the regression. This finding is consistent with the fact that variation in subjective uncertainty is largely firm-specific. We conclude that our results are neither driven by industry-composition effects, industry-specific or aggregate trends and cycles.

1.5.2 Comparing Cross Section and Time Series Variation in Subjective Uncertainty

The coefficients on positive and negative growth in column (6) in Table 1.5 effectively isolate large and asymmetric *time series* responses of firms to past growth. Perhaps interestingly, the asymmetric V-shaped response induced by time series responses is rather similar to that induced purely by cross sectional heterogeneity. To see this, consider Figure 1.5, where we show the fitted line from before and several regression lines to compare the two forces.

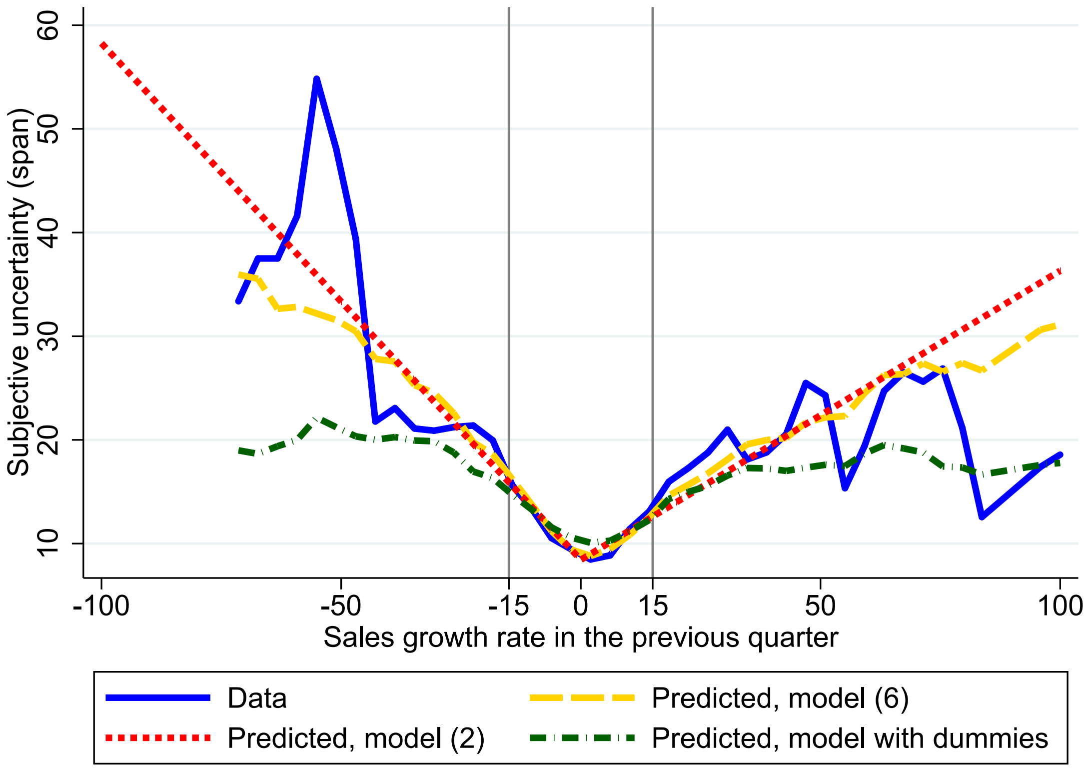
As a benchmark, the solid blue line is the nonparametric regression line fit to the data, and the dotted red line is the fitted line from the regression model in column (2) of Table 1.5, both already shown in Figure 1.3. The dashed yellow and the dash-dotted green lines are fit not to the data, but to clouds of predicted values from two parametric regressions.[18] In particular, the dashed yellow line is fit through the predicted values from the regression model in column (6) of Table 1.5. The dash-dotted green line is fit through the predicted values from a model with *only* the three classes of dummies, thus reflecting only cross sectional variation.

The main takeaway from Figure 1.5 is that all lines lie effectively on top of each other, especially within the interdecile range. In other words, time series and cross sectional variation induces the same V-shape, albeit through very different mechanisms. For the

[18] The collection of precise values comprise a cloud rather than, say, a line because growth is not the only regressor; there are also fixed firm characteristics. For example, for two firms that experienced the same sales growth rate in the previous quarter, the model in column (6) of Table 1.5 will predict different spans depending on the firms' size, trend, and turbulence.

time series response, the V follows directly from the difference in coefficients on positive and negative growth. For the cross section, the effect is more subtle and comes from the comovement of span and volatility documented in Table 1.3: firms with higher span also see higher absolute values of their growth rates (due to differences in size, trend or turbulence).[19]

Figure 1.5: Cross-sectional and time series relationships between uncertainty and past sales growth



Notes: Besides a linear fitted line with break at zero that corresponds to column (2) of Table 1.5 (dotted red line), the chart presents three non-parametric regression lines. Respectively, the nonparametric regression lines are based on the full sample (solid blue line), the cloud of predicted values of column (6) of Table 1.5 (dashed yellow line), and the cloud of predicted values from a model with size, trend, turbulence, and time-sector dummies as regressors (dash-dotted green line). The thin vertical lines mark the interdecile range that extends from −15% to 15%, see Table 1.E.1.

1.5.3 Subjective Uncertainty and Volatility in the Time Series

Section 1.4.4 showed that subjective uncertainty and volatility vary differently in the cross section of firms. How do subjective and statistical uncertainty compare in the

[19] In Appendix 1.F we also show that the V-shaped relationship between sales growth and subjective uncertainty holds separately, and in a quantitatively similar manner, for all firm-level subgroups: the four firm size groups, the four turbulence groups, and the three growth trend groups.

within-firm time series dimension? Table 1.6 compares our baseline regression of span on past growth and fixed characteristics – column (1) here reproduces column (6) of Table 1.5 – to an analogous regression for the absolute value of the firm's subjective forecast error, shown in column (2).

Table 1.6: Relation of subjective uncertainty and the absolute forecast error to past sales growth, firm characteristics, and additional controls

Dependent variable:	(1) span	(2) firms' abs(FE)	(3) span	(4) firms' abs(FE)	(5) span	(6) firms' abs(FE)
Negative sales growth rate in quarter $t-1$	-0.306***	-0.337***	-0.252***	-0.347***	-0.351***	-0.316***
	(0.0675)	(0.0689)	(0.0780)	(0.0689)	(0.0861)	(0.0777)
Positive sales growth rate in quarter $t-1$	0.180***	0.123**	0.171***	0.150***	0.229***	0.138***
	(0.0314)	(0.0529)	(0.0323)	(0.0506)	(0.0351)	(0.0483)
Dummy small firms	-3.959*	-0.632	-3.746**	0.396	-3.043	-0.631
	(2.178)	(1.545)	(1.843)	(1.511)	(2.062)	(1.626)
Dummy medium sized firms	-5.452**	-1.672	-5.821***	-0.983	-5.788***	-1.303
	(2.141)	(1.460)	(1.942)	(1.403)	(2.171)	(1.513)
Dummy large firms	-6.295***	-1.810	-6.619***	-1.298	-6.428***	-1.505
	(2.170)	(1.598)	(1.956)	(1.558)	(2.171)	(1.779)
Dummy 'bad' sales growth trend	2.248***	1.340*	1.688**	0.589	0.891	0.731
	(0.856)	(0.811)	(0.854)	(0.942)	(0.911)	(0.923)
Dummy 'good' sales growth trend	-0.434	1.417*	-0.440	1.722*	-1.284	1.329
	(0.645)	(0.826)	(0.680)	(0.957)	(0.817)	(0.942)
Dummy medium low turbulence	1.388**	1.802***	1.458**	1.837***	0.427	1.811***
	(0.591)	(0.356)	(0.663)	(0.491)	(0.729)	(0.501)
Dummy medium high turbulence	4.560***	4.160***	4.490***	4.069***	3.722***	3.694***
	(0.764)	(0.472)	(0.765)	(0.505)	(0.917)	(0.616)
Dummy high turbulence	6.748***	9.161***	5.835***	8.236***	4.098***	7.429***
	(0.969)	(0.953)	(0.974)	(0.994)	(1.124)	(1.038)
Expected sales growth rate for quarter t			0.0769**	0.0125	0.0849**	0.0276
			(0.0323)	(0.0517)	(0.0387)	(0.0480)
State of business (VAS) at the time of the survey			-0.0591***	0.00362	-0.0428**	0.00865
			(0.0185)	(0.0254)	(0.0215)	(0.0266)
Capacity utilization rate			0.00716	0.0122	-0.0190	0.0189
			(0.0265)	(0.0257)	(0.0254)	(0.0256)
Absolute forecast error in quarter t					0.0574	
					(0.0556)	
Span for quarter t						0.0764
						(0.0756)
Constant	11.37***	3.782**	8.832	2.444	9.372**	5.066*
	(2.154)	(1.484)	(7.002)	(5.952)	(4.097)	(2.917)
Other firm controls			YES	YES	YES	YES
Time-sector dummies			YES	YES	YES	YES
No. of observations	2762	1664	2561	1570	1533	1533
No. of firms	400	389	378	368	360	360
No. of parameters (excl. intercept)	10	10	218	203	205	204
R-squared	0.29	0.25	0.37	0.37	0.44	0.37

Notes: Results from pooled OLS regressions. span is our measure of subjective uncertainty and firms' abs(FE) denotes firms' absolute forecast error. The expected sales growth rate for quarter t is the answer to question 2.b of the survey (see Section 1.2.2). Other firm controls include the capacity utilization rate and dummies for the state of business, orders, stock of inventory, production changes, demand changes, order changes, price changes, credit appraisal, capacity utilization, and constraints to production. See Appendix 1.H for a detailed description. Standard errors in parentheses, clustered by firm; * p < 0.10, ** p < 0.05, *** p < 0.01.

Controlling for fixed characteristics, a firm that observes one percent worse negative growth in the previous quarter not only increases its span by 31 basis points, but also experiences, on average, a subjective forecast error that is 34 basis points higher in absolute value. In contrast, one percent higher positive growth increases span by 18 bp and the absolute value of the forecast error by 12 bp. The asymmetric V that emerges in the time series of firms' uncertainty is thus also present in firms' experience of shocks.

The differences between subjective uncertainty and volatility observed in the cross section appear to be largely orthogonal to the time series dynamics of span and growth. Indeed, the regression coefficients in columns (1) and (2) of Table 1.6 display the same patterns as columns (4) and (6) of Table 1.3: large firms and very turbulent firms are less uncertain than one might expect given the size of the shocks they face, and the asymmetric relationship between trend growth and uncertainty is a subjective phenomenon.

1.5.4 Controlling for Firm Actions and Expectations

What mechanism is behind the within-firm time series relationship between uncertainty and growth? One possible explanation is that uncertainty shocks are reflected in firm actions and hence growth. In particular, it may be that we can simply extend recent models of uncertainty-driven recessions to firm dynamics. The key feature of such models is that the stochastic process driving uncertainty is orthogonal to innovations to growth conditional on uncertainty, as in example (1.3)-(1.4) above.

An alternative interpretation of the data invokes learning or signal extraction on the part of firms, another special case of our general model (1.1)-(1.2). Suppose firms view growth itself as a signal of future business conditions. Many models of belief updating imply that a more unusual realization should increase uncertainty. For a concrete example, consider a regime switching model: the state of business follows a finite state Markov chain, and growth is given by a regime-dependent mean plus iid noise. A more unusual growth rate observation will typically lead the firm to perceive more uncertainty about its current estimate of the regime.

The key difference between the two candidate mechanism is the role of firm actions for growth. Under the uncertainty shock story, growth responds to persistent changes in uncertainty. Comovement between current uncertainty and past growth is thus induced by firms' past responses to uncertainty. In (1.3)-(1.4), there is no additional signal value to growth conditional on volatility last period. Under a learning story, in contrast, there may be *no* effect of current uncertainty on past firm actions.

The different role of firm actions for the two stories suggests a simple check: if the relationship between growth and uncertainty is induced by firms' actions, then controlling for firm actions in our regressions should alter the coefficients we find on past growth. We perform the check in column (3) of Table 1.6: here we augment the baseline regression in column with (1) with both time sector dummies as well as an additional set of controls that vary *over time at the firm level*.

The new controls are firms' expectations about their future sales growth, their assessment of the state of their business and their capacity utilization, as well as categorical variables that report orders, the stock of inventory, demand, production, prices, and credit conditions. The difference between these additional controls and the firm characteristics already included above is that the former vary at high frequency at the firm level. In particular, they capture actions the firm could have taken at the beginning or during the course of the quarter such as scale down production or increasing prices.[20]

The main result from column (3) is that the coefficients on growth are virtually unchanged, as predicted by a learning model. This is not because the new variables are uncorrelated with subjective uncertainty: on the contrary, the R-squared improves by 8 percentage points between columns (1) and (3). About half of this improvement comes from the inclusion of time varying firm level controls – this follows from a comparison with column (8) of Table 1.5. Nevertheless, the impact of the new controls appears to be orthogonal to the role of past growth in predicting subjective uncertainty. We conclude that the timing of growth, uncertainty and firm actions favors a learning interpretation of our time series facts, and provides little support for an uncertainty shock mechanism.

1.6 The Dynamics of Subjective Uncertainty

In this section, we further explore the dynamics of subjective uncertainty. Our approach is motivated by two properties of many common learning rules: we would expect higher forecast errors to increase uncertainty, and changes in uncertainty to propagate over time. In principle, these properties alone could induce a V-shaped relationship between uncertainty and growth. In Section 1.6.1 we therefore ask whether controlling for lagged forecast errors as well as lagged uncertainty affects the relationship between growth and uncertainty. The answer will help guide the choice among alternative models of belief updating. In Section 1.6.2 we check whether replacing forecast errors with an alternative measure of sales growth surprise changes our conclusions.

[20] Appendix 1.H provides a detailed list of the additional firm-level controls and their timing relative to quarter t, when span was uttered.

1.6.1 What Moves Subjective Uncertainty?

Table 1.7 digs more deeply into firms' time series response to growth. For the subsample of responses for which we observe a forecast for the previous quarter, we can decompose growth into forecast plus forecast error. We can therefore distinguish firms' responses to unanticipated change – as captured by their forecast error – and anticipated change already captured by their forecast. Formally, we proceed by including the forecast error of the previous quarter as an additional regressor.

Column (1) replicates column (6) of Table 1.5, our baseline result, now on the somewhat smaller sample for which we observe firm forecast errors: the V-shape of subjective uncertainty in previous-quarter sales growth is again present. Then, in column (2), we replace sales growth with previous-quarter forecast errors in sales growth: we find again a V-shape with somewhat smaller coefficients. We note that the R-squared of this regression declines slightly compared to column (1). Column (3) presents the results from a regression specification where both sales growth and the forecast error, in both cases allowing for asymmetry, are included. It is now the asymmetric V in sales growth that wins the horse race between change and unanticipated change, the latter losing asymmetry and statistical significance. Notice again that the R-squared in column (3) hardly improves compared to column (1).

Columns (4) to (6) repeat the same steps, but this time with lagged span included in the regression. We first note that subjective uncertainty displays a mild persistence because it depends on its own lag in all three specifications. With respect to the relevance of sales growth versus forecast error, the result is the same, even starker: in a horse race between these two regressors to determine subjective uncertainty, it is sales growth that enters with an asymmetric V, whereas the data do not ask for the forecast error over and above sales growth.

To understand why past growth "drives out" the past forecast error in these regressions, we compare group averages of span in a two-by-two table of high versus low absolute growth rates and high versus low absolute forecast errors. We compute these group averages as follows. To control for firm characteristics we first partial out the size, trend and turbulence dummies from span, absolute growth and absolute forecast errors leaving the conditional linear relationship between the latter three variables unchanged.[21] Since our partial-out regressions include an intercept, the resulting adjusted variables have mean zero.

[21] Technically, we invoke the Frisch-Waugh theorem which says that there are two equivalent ways to control for some variables z (here: the dummies) in an OLS regression of y (here: span) on x (here: past sales growth and past forecast error). Either regress y on x and z and take the coefficient of x.

Table 1.7: Relation of span to its own lag, past sales growth, and past forecast error

Dependent variable:	(1) span	(2) span	(3) span	(4) span	(5) span	(6) span
Subjective uncertainty in quarter $t-1$				0.273***	0.271***	0.276***
				(0.0706)	(0.0748)	(0.0695)
Negative sales growth rate in quarter $t-1$	-0.358***		-0.314***	-0.322***		-0.333***
	(0.0755)		(0.0825)	(0.0754)		(0.0910)
Positive sales growth rate in quarter $t-1$	0.148***		0.0990**	0.138***		0.0936*
	(0.0394)		(0.0450)	(0.0381)		(0.0478)
Negative forecast error in quarter $t-1$		-0.232***	-0.0599		-0.166***	0.0167
		(0.0573)	(0.0567)		(0.0586)	(0.0607)
Positive forecast error in quarter $t-1$		0.130***	0.0747		0.116***	0.0641
		(0.0392)	(0.0488)		(0.0363)	(0.0498)
Size, trend, and turbulence dummies	YES	YES	YES	YES	YES	YES
Constant	11.70***	11.61***	11.48***	8.587***	8.719***	8.465***
	(2.562)	(2.610)	(2.544)	(2.055)	(2.039)	(2.008)
No. of observations	1520	1520	1520	1489	1489	1489
No. of firms	373	373	373	367	367	367
No. of parameters (excl. intercept)	10	10	12	11	11	13
R-squared	0.35	0.32	0.35	0.40	0.38	0.41

Notes: Results from pooled OLS regressions. They are based on the sample of firms with at least five answers to question 1. In addition, we require an answer to question 2.b to compute the firms' forecast error for two adjacent observations of a firm. This results in the already familiar sample of 1,664 observations. We further need the lag of the forecast error, and hence, three consecutive observations in a firms' time series. Requiring span to be available as well, we are left with 1,520 observations. In columns (4) to (6) we additionally require the lag of span and we arrive at 1,489 observations. Standard errors in parentheses, clustered by firm. * p < 0.10, ** p < 0.05, *** p < 0.01.

Subsequently, we split adjusted absolute growth and adjusted absolute forecast errors into observations above and below their means, thereby defining the four quadrants shown in the left panel of Table 1.8, respectively, and compute average span for each quadrant. For example, the upper left value of -1.82 means that a firm which, after controlling for firm characteristics, experience in period $t-1$ a below-average absolute growth rate and a below-average absolute forecast error, reports a 1.82 percentage points smaller span than the average firm in period t. In addition, we count the number of observations that fall in each quadrant (in square brackets below average span).

The first takeaway from the upper left panel of Table 1.8 is that uncertainty as measured by span is relatively low (high) if both absolute growth and absolute forecast errors are relatively low (high). Hence, a firm is relatively certain if it experiences a small absolute growth rate near its expectations and it is relatively uncertain if it experiences a large absolute growth rate far away from what it expected. Most observations (665+410=1075 of 1520 and thus 71%) fall in these two cells reflecting that sales growth is difficult to predict, so that low (high) absolute forecast errors and low (high) absolute growth go hand in hand.

Alternatively, first regress y on z and x on z and then regress the residuals of these two regressions on each other.

But what happens in the upper right and lower left cells? Concerning the upper right cell, a small absolute growth rate that comes as a big surprise almost does not alter span. This suggests that firms which incorrectly expected something "big" to happen do not experience heightened uncertainty even though the size of their forecast error is large because the signal they receive tells them that they are in calm territory. By contrast, the lower left cell tells us that a large absolute growth rate increases uncertainty to a noticeable, while not statistically significant, amount even if it comes largely expectedly. Again, it thus appears to be the signal conveyed by the absolute growth rate which shapes uncertainty and not the expectational error.[22]

Table 1.8: Two-by-two tables of span

	Full sample		*Only neg. growth and neg. FE*	
	low abs. FE	high abs. FE	low abs. FE	high abs. FE
After partialling out size, trend, and turbulence dummies				
low abs. growth	-1.82^{***} [obs: 665]	-0.19 [obs: 188])	-2.04^{***} [obs: 127]	-0.02 [obs: 68]
high abs. growth	0.64 [obs: 257]	2.63^{***} [obs: 410]	2.01^{*} [obs: 62]	3.29^{***} [obs: 170]
After partialling out size, trend, and turbulence dummies, and lagged span				
low abs. growth	-1.38^{***} [obs: 637]	-0.82 [obs: 188])	-1.71^{***} [obs: 125]	-0.20 [obs: 68]
high abs. growth	0.52 [obs: 242]	2.14^{***} [obs: 422]	1.51 [obs: 61]	3.01^{***} [obs: 166]

Notes: The cells show group-specific average span and, in brackets below, the number of observations per cell. The upper panel of the table is based on the residuals from a regression of span on size, trend, and turbulence dummies (1,520 observations). The lower panel is based on the residuals from regressing span on size, trend, and turbulence dummies, and additionally on its own lag (1,489 observations). These two parts refer to the samples used in columns (1) to (3) and (4) to (6) of table 1.7, respectively. The table is split in two parts: the left part concerns the full sample, and the right part the subset of firm-time observations, for which both sales growth and forecast error are negative. In each part, the numbers in each panel refer to four quadrants. To define these quadrants, we first regress absolute sales growth and absolute forecast error on size, trend, and turbulence dummies for the statistics in the upper panel of the table, and on the same dummies and lagged span in the lower panel. The quadrants are then defined by the mean values of the residuals of the absolute sales growth and the absolute forecast error regressions.* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

To better understand this finding, we next distinguish between positive and negative growth. The upper right panel of Table 1.8 reports average span using only those

[22] This interpretation is supported by comparing the fit of two simple models, after partialling out size, trend and turbulence dummies from span, absolute growth and absolute forecast errors. Model 1 fits two group means to span with groups being defined by low and high absolute forecast errors, while model 2 fits two group means to span with groups being defined by low and high absolute growth. Hence model 1 reflects the column dimension of the upper left quadrant of Table 1.8 while model 2 mirrors the row dimension. It turns out that the fit of model 1 is worse than the fit of model 2 in all four quadrants, particularly so in the lower left cell. Overall, model 1 has an R-squared of 2.8% whereas model 2 has an R-squared of 3.9%.

observations falling into the respective quadrants that exhibit negative growth and negative forecast error. By comparing the panels we can thus assess the asymmetry of the relationships between span and its drivers. It turns out that the differences are moderate in all cells but the lower left one where average span is much larger than in the full sample: a large negative growth rate that is slightly larger than expected entails a strong increase in span by 2 percentage points. Hence, it is firms in a gloom situation–expecting an unusually bad outcome and experiencing and even slightly worse realization–which drive the lower left cell.[23]

The lower panel of Table 1.8 shows that the preceding results are robust to including lagged span in the set of controls. To summarize, we find that subjective forecast errors are driven by past sales growth rather than past forecast errors. While these two regressors are similar as sales forecasts appear difficult, there is a notable number of observations exhibiting small (large) absolute sales growth and large (small) absolute forecast error. In these cases, sales growth is a better predictor of span particularly for firms in a gloomy situation.

What is the economic mechanism that makes firms more uncertain especially after a negative previous-quarter sales growth rather than a negative sales growth surprise? A possible interpretation is that negative sales growth indicates a loss of customers in an environment where building up customer relationships is costly and not necessarily successful. Hence, affected firms do not know whether and which new customers can be found in the months going forward, making them more uncertain with respect to future sales growth.

1.6.2 Another Surprise Measure

As a robustness check we ask whether the results remain unchanged if we replace previous-quarter forecast error by an alternative measure of sales growth surprise. To this end, we construct a variable that measures the distance of the previous-quarter growth rate to the forecast interval stated one quarter before as follows: it takes the value of zero if the growth rate falls into the interval, the distance of the growth rate to the upper interval limit (the best case) if the growth rate falls above the interval, and the distance to the lower interval limit (the worst case) if the growth rate falls below the interval. Thereby, we measure the surprise intensity for those firms that see their previous-quarter growth rate outside their forecast interval stated one quarter before.

[23] In fact, the average span in the lower left cell of the complementary group of firms that do not exhibit both negative growth and negative forecast error is 0.2 and thus almost indistinguishable to the average of zero.

Table 1.9 reports the results of regressions of span on the previous-quarter growth rate and the previous-quarter surprise measure just defined. To account for asymmetry we split both regressors into their positive and negative parts. Note that a positive (negative) surprise is the distance of the growth rate to the upper (lower) interval limit if the growth rate falls above (below) the interval. A regression of span on the surprise measure without any controls shows there is again a highly significant, asymmetric V-type relationship (column 1). Including size, trend, and turbulence dummies flattens the V but leaves the negative arm significant (column 2). However, adding the sales growth rate yields the same "driving out" result reported in Section 1.6.1: both parameters of the surprise measure become quantitatively small and statistically insignificant while the parameters of the sales growth rate exhibit the asymmetric V. Columns (4) to (6) replicate this outcome when lagged span is included as an additional regressor.

Table 1.9: Relation of span to its own lag, past sales growth, and past outside deviation from worst or best case

Dependent variable:	(1) span	(2) span	(3) span	(4) span	(5) span	(6) span
Subjective uncertainty in quarter $t-1$				0.460***	0.388***	0.283***
				(0.0744)	(0.0786)	(0.0743)
Negative sales growth rate in quarter $t-1$		-0.574***	-0.348***		-0.367***	-0.269***
		(0.0789)	(0.0687)		(0.0778)	(0.0741)
Positive sales growth rate in quarter $t-1$		0.283***	0.176***		0.148***	0.118**
		(0.0461)	(0.0460)		(0.0527)	(0.0500)
Deviation from worst case forecast in quarter $t-1$	-0.529***	-0.0600	-0.0659	-0.425***	-0.137*	-0.122
	(0.107)	(0.103)	(0.107)	(0.0817)	(0.0778)	(0.0839)
Deviation from best case forecast in quarter $t-1$	0.191***	-0.0305	-0.0355	0.188***	0.0777	0.0425
	(0.0542)	(0.0709)	(0.0605)	(0.0467)	(0.0681)	(0.0603)
Size, trend, and turbulence dummies	YES	YES	YES	YES	YES	YES
Constant	10.70***	8.213***	11.89***	5.341***	4.721***	8.536***
	(0.476)	(0.491)	(2.627)	(0.815)	(0.669)	(2.043)
No. of observations	1513	1513	1513	1513	1513	1513
No. of firms	372	372	372	372	372	372
No. of parameters (excl. intercept)	2	4	12	3	5	13
R-squared	0.098	0.22	0.35	0.31	0.35	0.41

Notes: Results from pooled OLS regressions. They are based on the sample of firms with at least five answers to question 1. In addition, we require an answer to question 2.a to compute the distance of a firms' realization from below the worst case or from above the best case forecast for two adjacent observations of a firm. We further need the lag of this distance variable, and hence, three consecutive observations in a firms' time series. Requiring span to be available as well, we are left with 1,513 observations. The variable "Deviation from worst (best) case forecast in quarter $t-1$" has value zero if the past realized sales growth rate was inside the forecast interval. Standard errors in parentheses, clustered by firm. * p < 0.10, ** p < 0.05, *** p < 0.01.

1.7 Volatility

The goal of this section is to compare the dynamics of "statistical" uncertainty experienced by firms to that of subjective uncertainty perceived by firms. We have already seen in Section 1.5.3 that the projection of the absolute size of forecast errors on past growth – controlling for fixed characteristics – yields coefficients that are quite similar to the coefficients of our baseline span regression. We now ask to what extent firms' updating of subjective uncertainty studied in the previous section resembles the dynamic behavior of the conditional volatility of shocks. In terms of the framework of Section 1.3.2, how similar are the dynamics of the subjective and statistical uncertainty measures σ and $\hat{\sigma}$?

The section proceeds as follows. As a preliminary step, we distinguish between the two sources of firm forecast errors discussed in Section 1.3.2: bias and conditional volatility. In Section 1.7.1, we thus "clean" subjective forecast errors by removing firm fixed effects of forecast bias already documented in Section 1.4.4. We also provide an alternative benchmark set of forecast errors from a statistical model. That model is by construction unbiased, although it may also be based on less information than what is available to firms. Its purpose is to analyze whether firm's subjective forecasts are special, or whether they just reflect generic properties of the data.

We then estimate dynamic models of conditional volatility to provide a statistical counterpart to the regressions of span on lagged span, past growth, past forecast errors as well as fixed firm characteristics reported in Section 1.6.1. To this end, in Section 1.7.2 we estimate models of conditional volatility for both the cleaned subjective errors and for the statistical errors. Section 1.7.3 finally compares the dynamics of all three measures of firm uncertainty. To preview the results, we show that the dynamics of subjective uncertainty and "objective" conditional volatility are similar in some dimensions but differ in others. Similarities exist mainly in the time series dimension. They include mild but statistically significant persistence, irrelevance of lagged forecast errors, and importance of lagged absolute sales growth, especially if it is negative. Differences are pronounced in the cross section dimension. Indeed, volatile and large firms are not uncertain enough—seem to underestimate the volatility they face—, while firms on a bad sales growth trend are more uncertain than conditional volatility suggests.

The sample used throughout this Section is composed such that we can estimate dynamic models of the conditional volatility of firms' forecast errors. We start from the forecast sample defined in Table 1.C.1 in Appendix 1.C which includes all quarter-firm observations for which a forecast is available but not necessarily a span. Using this sample we construct forecast errors. To model dynamics, we further require a lagged forecast error and thus three adjacent observations. This reduces the sample to 949 observations plus 380 pre-sample observations on which we condition in the dynamic models. Hence, we use 1,329 observations altogether.

1.7.1 Cleaned Subjective and Statistical Forecast Errors

In order to clean observed forecast errors of firm-specific bias, we estimate regressions of survey-provided forecast errors on fixed characteristics and use the resulting residuals as our cleaned errors. In terms of the representation (1.5), this removes the part of the bias $b(s_t^i, x^i)$ that depends on the fixed characteristics x^i. We do this in order to focus on belief dynamics. In particular, we are interested in the response of span to temporary surprises experienced by firms, not surprises they routinely experience because they make biased forecasts.[24]

Table 1.10: Relation of sales growth to past sales growth and firm characteristics

Dep. variable: sales growth t to $t+1$	(1)	(2)	(3)	(4)	(5)	(6)
Negative sales growth in quarter $t-1$	-0.269*	-0.141	-0.130			
	(0.141)	(0.145)	(0.128)			
Positive sales growth in quarter $t-1$	-0.0357	0.0392	0.0495			
	(0.0907)	(0.0978)	(0.0856)			
Dummy small firms	5.314***	7.798***		5.298***	7.776***	
	(1.815)	(2.255)		(1.747)	(2.192)	
Dummy medium sized firms	4.996***	7.408***		5.082***	7.432***	
	(1.669)	(2.136)		(1.607)	(2.073)	
Dummy large firms	5.000***	7.228***		5.013***	7.159***	
	(1.689)	(2.127)		(1.632)	(2.057)	
Dummy 'bad' sales growth trend	-7.143***			-6.726***		
	(0.967)			(0.936)		
Dummy 'good' sales growth trend	8.005***			8.253***		
	(1.095)			(1.112)		
Dummy medium low turbulence	-1.717***	-2.068**		-1.434***	-1.827*	
	(0.572)	(0.959)		(0.500)	(0.929)	
Dummy medium high turbulence	0.427	-0.882		0.973	-0.411	
	(0.833)	(1.117)		(0.642)	(0.968)	
Dummy high turbulence	-0.143	-0.274		1.343	0.954	
	(1.561)	(1.691)		(1.149)	(1.384)	
Sales growth in quarter $t-1$				-0.132***	-0.0365	-0.0247
				(0.0414)	(0.0455)	(0.0462)
Intercept	-3.243**	-5.059**	1.164	-2.881*	-4.663**	2.015***
	(1.610)	(2.092)	(0.811)	(1.534)	(2.011)	(0.439)
No. of observations	1329	1329	1329	1329	1329	1329
No. of firms	292	292	292	292	292	292
R-squared	0.12	0.021	0.0047	0.12	0.018	0.001
AIC	10696.7	10837.8	10848.1	10702.2	10839.9	10851.5
BIC	10753.8	10884.5	10863.7	10754.1	10881.5	10861.9

Notes: Results from pooled OLS regressions. They are based on the sample of firms with at least five answers to question 1. In addition, we require an answer to question 2.b to compute the firms' forecast error for two adjacent observations of a firm. For comparability with the results of the power GARCH models, we further need the lag of the forecast error, and hence, three consecutive observations in a firms' time series. This leaves us with 1329 observations. Standard errors in parentheses, clustered by firm. * p < 0.10, ** p < 0.05, *** p < 0.01.

[24] The regressions are based on the sample of firms with at least five observations of sales growth. In addition, to compute a forecast error we need two adjacent observations of a firm (a sales growth forecast in quarter $t-1$ followed by a sales growth rate in quarter t). For comparability with the results of the GARCH models below, we further need the lag of the forecast error, and hence, three consecutive observations in a firm's time series. This leaves us with 1329 observations.

Specifically, we regress the survey-provided forecast error on our previously defined size, trend, and turbulence dummies as well as their pairwise interactions. To prevent overfitting, we apply the LASSO estimator (Tibshirani, 1996) to select a subset of relevant regressors.[25] We choose the LASSO tuning parameter τ by minimizing Mallows's C_p statistic as suggested by Efron et al. (2004). The LASSO then selects 11 predictors. In particular, denote the high and low growth dummies by gd_1 and gd_3, the medium low, medium high and high volatility dummies by vd_1, vd_2, and vd_3, and the small, medium and large size dummies by sd_1, sd_2, and sd_3, respectively. The selected predictors are then gd_1, gd_3, as well as the interactions $sd_1 \cdot gd_1$, $sd_2 \cdot gd_1$, $sd_2 \cdot gd_3$, $sd_1 \cdot vd_2$, $sd_1 \cdot vd_3$, $sd_2 \cdot vd_4$, $sd_3 \cdot vd_4$, $gd_1 \cdot vd_4$, $gd_3 \cdot vd_4$.

To obtain a bias-adjusted forecast error we construct the OLS residuals of a regression of the forecast error on these predictors. In doing so, we follow Belloni and Chernozhukov (2013) who show that it is advantageous in terms of bias to let the LASSO select the relevant regressors and subsequently apply OLS to estimate the regression coefficients, see Lehrer and Xie (2017) for a related application. We find that the R-squared of the OLS regression is 0.04 which indicates that biased forecasting is not pervasive but rather an issue for small groups of firms.

To provide an alternative benchmark for firm-level forecast errors, we construct a set of statistical forecast errors by using our own statistical forecasting models. In particular, we regress sales growth on its own lag as well as size, growth, and turbulence dummies. We allow for an asymmetric response to past growth, as in our span regressions. We also note that since trend and turbulence are defined using sample moments, they are, strictly speaking, not part of the information set of a firm. At the same time, firms have longer samples than we have that speak to their trend growth and volatility. Our assumption here is that trend and turbulence reflect medium term prospects known to firms.

The regression coefficients are reported in column (1) of Table 1.10. For robustness, we try a number of specifications. In column (2), we leave out the growth trend dummies from the set of regressors as they might be very dominant. In column (3) and we also estimate a simple asymmetric AR(1) model. In columns (4)-(6), we replicate the first three specifications but restrict the effect of past sales growth to be symmetric. Forecast errors from all six specifications are highly correlated, with correlation coefficients at

[25] The LASSO is a standard shrinkage estimator popular in "big data" analysis (Varian, 2014) as it recovers the correct (sparse) model with high probability (Hastie et al., 2017). By requiring that the L_1 norm of the coefficient vector does not exceed a certain threshold, say, τ, the LASSO restricts many coefficients to zero and thereby helps to balance the bias-variance tradeoff seen in forecasting. This is why the LASSO and related estimators are widely applied for economic forecasting in data-rich environments (Bai and Ng, 2008; Manzan, 2015; Elliott and Timmermann, 2016).

0.93 or above. Moreover, both AIC and BIC favor specification (1). In what follows, we report only results based on that specification.

1.7.2 Measuring Conditional Volatility

How does subjective uncertainty compare to conditional volatility, or more generally, uncertainty measured by an econometrician? We have identified subjective uncertainty with span, the difference between best and worst case scenarios. A natural "objective" counterpart is the length of a forecast interval constructed by the econometrician, for example the difference between an upper and lower quantile of the conditional distribution of forecast errors. In the broad class of distributions of the location-scale family, that length is a multiple of the standard deviation which we thus choose as our measure of volatility.

We study the conditional volatility of both types of forecast errors defined in Section 1.7.1. In both cases, we select and estimate a volatility model that optimally describes the data as indicated by information criteria.

Let $\tilde{e}_{it}$ be the bias-adjusted forecast error of firm i in quarter t, and denote its conditional standard deviation by σ_{it}. Our choice of functional form mirrors our analysis of subjective uncertainty in Section 1.6.1: we write σ_{it} as a function of past growth, past forecast errors and fixed firm characteristics. We thus use a restricted version of the power GARCH model (Ding et al., 1993; Ding and Granger, 1996; Karanasos and Kim, 2006). While the unrestricted power GARCH model conditions σ_{it}^{p} on past information, $I_{i,t-1}$, where p is a power coefficient to be estimated, we impose the restriction $p = 1$ and thus model the conditional standard deviation.

Our conditional volatility model then has the general form

$$\tilde{e}_{it} = \mu + \varepsilon_{it}, \qquad \varepsilon_{it}|I_{i,t-1} \sim N(0, \sigma_{it}^2) \tag{1.7}$$

with a conditional standard deviation equation

$$\sigma_{it} = \exp(\beta_0 + \beta_1' x_{it}) + \alpha_1(|\varepsilon_{i,t-1}| + \gamma\varepsilon_{i,t-1}) + \alpha_2\sigma_{i,t-1}. \tag{1.8}$$

The mean equation (1.7) includes an intercept to account for a nonzero sample mean that arises because we apply the bias adjustment of the forecast error to all 1,329 observations but estimate the volatility model on an effective sample of those 949 observations for which a lag is available. The conditional volatility equation (1.8) allows for an asymmetric effect of the past absolute forecast error measured by the coefficient γ, as asymmetry was found to be relevant in explaining subjective uncertainty. However, we do not expect a strong effect here because the empirical unconditional distribution of the bias-adjusted forecast errors is essentially symmetric with a sample skewness of 0.1.[26]

We add two types of explanatory variables contained in vector x_{it} to the conditional volatility equation. They enter the model through an exponential link function to ensure effects are always positive. The first type consists of size, trend, and turbulence dummies which are essentially time-invariant and thus control for different levels of conditional volatility for subgroups of firms. Our analysis above indicated that these dummies are sufficient to capture the bulk of time-invariant heterogeneity in subjective uncertainty. The second type includes positive and negative sales growth in the previous quarter which we found to be highly relevant to explain subjective uncertainty.

To find a reliable parsimonious specification, we estimate several restricted versions of (1.7)-(1.8) by maximum likelihood. Specification (1) adds no additional control variables ($\beta_1 = 0$), specifications (2)-(4) allow only for size, trend and turbulence dummies, respectively, specification (5) allows for only positive and negative sales growth rate in the previous quarter, and (6) adds all variables together. All specifications are estimated either assuming symmetric effects of past forecast errors ($\gamma = 0$) or allowing for asymmetry (γ unrestricted).

To select among these specifications, we use two information criteria, AIC and BIC, which are commonly used in applied papers (Nelson, 1991; Zivot, 2009). In finite samples the BIC typically favors overly sparse models, while the AIC picks models with a more generous number of parameters, see Efron et al. (2004, pp. 230-235) for a general discussion and Lütkepohl (2005) for asymptotic and simulation evidence in a time series context. Hence, the models chosen by AIC and BIC may be thought of giving upper and lower bounds in terms of richness of parametrization.

The results reported in Table 1.11 suggest that the inclusion of turbulence dummies, whether by themselves in specification (4) or jointly with the other control variables in specification (6), is essential for model fit: all other specifications generate much larger information criteria. Deciding between specifications (4) and (6) is more tricky. In both the symmetric and the asymmetric case, the AIC favors the inclusion of all controls while the BIC picks the turbulence dummies alone. However, the differences in terms of AIC are large (29.81 and 32.42) while the differences in terms of BIC are small (4.19 and 1.57). Given that the BIC tends to select overly parsimonious models

[26] A test of the null hypothesis that the population skewness is zero cannot be rejected (p-value of 0.2).

Table 1.11: Model selection criteria for different specifications of the conditional volatility model

	Symmetric $\gamma = 0$			Asymmetric $\gamma \neq 0$		
Specification	k	AIC	BIC	k	AIC	BIC
(1) no controls	4	7,256.39	7,275.81	5	7,253.13	7,277.41
(2) only size dummies	7	7,249.95	7,283.94	8	7,248.10	7,286.94
(3) only growth trend dummies	6	7,173.30	7,202.43	7	7,174.46	7,208.45
(4) only turbulence dummies	7	6,901.40	6,935.38	8	6,903.38	6,942.22
(5) only sales growth rate	6	7,106.90	7,136.03	7	7,104.63	7,138.62
(6) all controls	14	6,871.59	6,939.57	15	6,870.96	6,943.79

Notes: k denotes the number of parameters. Equations 1.7 and 1.8 describe the model of conditional volatility. All specifications are estimated by maximum likelihood using 949 observations.

and based on the classification of Kass and Raftery (1995) that only BIC differences of more than 6 are "strong", on balance specification (6) is preferred.

Whether to allow for symmetric or asymmetric effects of past forecast errors is also difficult to decide as the differences in AIC and BIC are small. We therefore report the coefficient estimates of both specifications in columns (1) and (2) of Table 1.12. It turns out that the asymmetry parameter γ is not statistically different from zero while the estimates of the other coefficients are largely unaffected by restricting it to zero. This is not unexpected as the unconditional skewness is small. We thus conclude that the symmetric specification (6) is a sufficient description of the conditional volatility process that drives the data.

We refer to the OLS residuals from our preferred forecasting regression as "statistical" forecast errors and fit the same symmetric and asymmetric volatility models as for the firms' forecast errors, see columns (3) and (4) of Table 1.12. Again, the asymmetry parameter is not significantly different from zero, and restricting it to zero leaves the other parameter estimates fairly unchanged. Therefore, we take the symmetric specification—which is unanimously favored by the information criteria—as a sufficient description of the conditional volatility process that characterizes the statistical forecast errors.

1.7.3 Comparison of Subjective Uncertainty and Conditional Volatility

We are now ready to compare subjective uncertainty as measured by the span between the best case and worst case scenarios with our two statistical measures of conditional volatility. For the latter, we use the predicted conditional standard deviation of our

Table 1.12: Conditional volatility specification (1.8) estimated by maximum likelihood

Dependent variable:	Firms' forecast errors		Statistical forecast errors	
	(1)	(2)	(3)	(4)
Mean equation				
Intercept (μ)	0.298	0.291	0.171	0.122
	(0.252)	(0.251)	(0.270)	(0.281)
Volatility equation: baseline parameters				
Lagged absolute FE (α_1)	0.0852*	0.102*	0.00830	0.00918
	(0.0511)	(0.0538)	(0.0682)	(0.0579)
Lagged volatility (α_2)	0.235***	0.215***	0.236**	0.229***
	(0.0874)	(0.0799)	(0.0921)	(0.0824)
Asymmetry (γ)	0	0.478	0	3.359
	(.)	(0.317)	(.)	(21.85)
Volatility equation: parameters of exogenous regressors				
Negative sales growth in $t-1$	-0.0286***	-0.0309***	-0.0259***	-0.0278***
	(0.00910)	(0.00879)	(0.00792)	(0.00801)
Positive sales growth in $t-1$	0.0131**	0.0107*	0.00710	0.00468
	(0.00515)	(0.00576)	(0.00522)	(0.00605)
Dummy small firms	-0.139	-0.138	-0.142	-0.127
	(0.118)	(0.119)	(0.0867)	(0.0884)
Dummy medium sized firms	-0.223**	-0.230**	-0.182**	-0.170**
	(0.105)	(0.105)	(0.0744)	(0.0766)
Dummy large firms	-0.248**	-0.269**	-0.170**	-0.156*
	(0.111)	(0.111)	(0.0822)	(0.0871)
Dummy 'bad' sales growth trend	0.194**	0.167*	-0.0281	-0.0456
	(0.0882)	(0.0858)	(0.0652)	(0.0673)
Dummy 'good' sales growth trend	0.199**	0.209**	0.0648	0.0818
	(0.0948)	(0.0958)	(0.0815)	(0.0857)
Dummy medium low volatility	0.504***	0.506***	0.518***	0.517***
	(0.0867)	(0.0886)	(0.0725)	(0.0708)
Dummy medium high volatility	0.794***	0.797***	0.873***	0.879***
	(0.0873)	(0.0874)	(0.0684)	(0.0674)
Dummy high volatility	1.336***	1.322***	1.519***	1.520***
	(0.110)	(0.111)	(0.101)	(0.0964)
Intercept (β_0)	1.101***	1.125***	1.204***	1.199***
	(0.180)	(0.167)	(0.151)	(0.146)
No. of observations	949	949	949	949
No. of firms	292	292	292	292

Notes: Results from panel power GARCH models from equations 1.7 and 1.8 that describe the conditional standard deviation of firms' forecast errors in columns 1 and 2, and of statistical forecast errors in columns 3 and 4. In contrast to the symmetric models in columns 1 and 3, columns 2 and 4 allow for asymmetric effects. All specifications are estimated by maximum likelihood using 949 observations and 380 pre-sample observations on which we condition as explained below Table 1.10. Standard errors in parentheses, clustered by firm. * p < 0.10, ** p < 0.05, *** p < 0.01.

preferred symmetric specification (6). Descriptive statistics for all three measures are displayed in Table 1.13. A first notable result is that the distributions of the predicted conditional standard deviations of the firms' and the statistical forecast errors are remarkably similar. In fact, the correlation of the two volatility predictions is 0.97. Furthermore, we find that the average subjective uncertainty as measured by span is only 25 percent larger than the average of the predicted conditional standard deviations.

Table 1.13: Summary statistics for measures of subjective uncertainty and conditional volatility

Variable	N	Mean	Std. Dev.	P10	P25	P50	P75	P90
Span between worst and best case forecast	932	12.1	9.8	4	5	10	15	25
Predicted conditional volatility of firms' forecast errors	932	9.7	7.2	3.5	4.8	7.5	12.3	18.3
Predicted conditional volatility of statistical forecast errors	932	9.7	7.3	3.4	4.2	7.2	12.2	19.8

Notes: The predicted conditional volatility of firms' forecast errors and of statistical forecast errors stem from the symmetric power GARCH specifications in columns 1 and 3 of table 1.12, respectively. The number of usable observations shrinks from 949 as reported in Table 1.12 to 932 here because 17 quarter-firm observations we used to construct forecast errors have either a missing upper or lower interval bound, or both, in the data, and thus we cannot compute a span for these observations.

In a final step, we compare the dynamics of subjective uncertainty to the dynamics of conditional volatility. Since the volatility models link the conditional standard deviation to past sales growth and the dummies via an exponential function that ensures nonnegativity, we base our comparion on average partial effects. Formally, we compute, for each right-hand-side variable $x_{j,it}$ of the volatility equation (1.8), the average partial effect

$$APE_j = \sum_i \sum_t \frac{\partial \sigma_{it}}{\partial x_{j,it}}$$

and report them in columns (2) and (3) of Table 1.14 while column (1) replicates the coefficient estimates of the dynamic linear model for span reported in column (6) of Table 1.7 with the only difference that we replace the two insignificant regressors "positive past forecast error" and "negative past forecast error" by the single regressor "absolute forecast error" to conform with the specification of the volatility models.

The results indicate that the dynamics of subjective uncertainty and "objective" conditional volatility are remarkably similar. There is mild but statistically significant persistence; lagged forecast errors are largely irrelevant; and lagged absolute sales growth has an asymmetric effect with large negative realizations being roughly twice as important than large positive realizations. Hence, when forming uncertainty beliefs

Table 1.14: Comparison of subjective uncertainty and conditional volatility

	(1) Subjective uncertainty (span)	(2) Conditional volatility of firms' forecast errors	(3) Conditional volatility of statistical forecast errors
Uncertainty/volatility in $t-1$	0.270***	0.235***	0.236***
	(0.0699)	(0.0874)	(0.0921)
Absolute forecast error in $t-1$	0.0373	0.085*	0.008
	(0.0383)	(0.051)	(0.068)
Negative sales growth in $t-1$	-0.285***	-0.223***	-0.220***
	(0.0768)	(0.073)	(0.064)
Positive sales growth in $t-1$	0.112***	0.102**	0.060
	(0.0422)	(0.043)	(0.044)
Dummy small firms	-3.507*	-1.227	-1.316
	(2.066)	(1.068)	(0.811)
Dummy medium sized firms	-3.920*	-1.891	-1.656**
	(2.056)	(0.947)	(0.709)
Dummy large firms	-4.562**	-2.073**	-1.550*
	(2.022)	(1.006)	(0.790)
Dummy 'bad' sales growth trend	2.219***	1.498**	-0.234
	(0.780)	(0.706)	(0.540)
Dummy 'good' sales growth trend	-0.432	1.542**	0.565
	(0.530)	(0.756)	(0.727)
Dummy medium low turbulence	0.660	2.216***	2.294***
	(0.523)	(0.459)	(0.361)
Dummy medium high turbulence	3.714***	4.094***	4.714***
	(0.773)	(0.634)	(0.525)
Dummy high turbulence	4.528***	9.462***	12.057***
	(0.883)	(1.314)	(1.552)
No. of observations	1489	949	949

Notes: The first column displays pooled OLS regression coefficients, with clustered standard errors listed below the coefficients. This regression is comparable to column (6) of Table 1.7. The predicted conditional volatility of firms' forecast errors and of statistical forecast errors stem from the symmetric power GARCH specifications in columns 1 and 3 of table 1.12, respectively. The second and third columns show average partial effects from equation 1.8, with standard errors listed below the coefficients. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

firms appear to have a pretty realistic impression of the dynamics that characterize the underlying data.

In contrast, subjective uncertainty and conditional volatility differ markedly in some cross sectional dimensions. Most importantly, firms operating in a highly turbulent environment report, relative to firms operating in a calm environment, a subjective uncertainty that is on average 4.5 percentage points higher while the difference in terms of the conditional volatility of their forecast errors and the statistical forecast errors amounts to 9.5 and 12.1 percentage points, respectively. Hence, volatile firms are more uncertain than others but not quite enough—they seem to underestimate the volatility they face. We also observe an opposite overestimation effect: firms on a bad sales growth trend are more uncertain than conditional volatility suggests, while larger firms feel more certain than justified by conditional volatility.

To summarize, an average firm's updating of subjective uncertainty over time closely resembles the dynamics of conditional volatility, while its level of uncertainty appears to be fairly small on average being of roughly the same order of magnitude as the conditional standard deviation of their forecast error and in several cases fails to adequately reflect the environment the firm is operating in.

1.8 Conclusion

This paper provides survey evidence on firms' subjective uncertainty about future sales growth from a new panel data set of the German manufacturing sector. In particular, we measure managers' perceived uncertainty as the difference between their best and worst case forecast of one-quarter-ahead sales growth. After documenting that firms' subjective uncertainty varies both over time and in the cross section, our main result is that uncertainty reflects change. Firms perceive higher uncertainty after larger negative and larger positive sales growth, with a stronger effect for negative realizations. Moreover, firms that consistently grow or shrink and those with more volatile sales growth are more uncertain.

Using firms' forecast errors and predictions from a panel GARCH model, we compare subjective uncertainty to realized and conditional volatility. In the cross section of firms, subjective uncertainty differs from experienced volatility: fast-growing and large firms perceive lower uncertainty than fast-shrinking and small firms, respectively, even if they face shocks of similar size. However, conditional volatility is similar to subjective uncertainty in the time series: both are mildly persistent and increase more after very low compared to very high sales growth realizations.

These findings highlight the importance of idiosyncratic variation in firms' uncertainty during normal times. They also contribute to a discussion in the time series literature of uncertainty shocks by providing micro evidence for feedback effects between uncertainty and growth. The comparison of managers' subjective uncertainty with realized volatility and model-based conditional uncertainty helps to better understand firm behavior. Our results inform common assumptions in existing work and can be incorporated into new models of firm dynamics.

Appendix

1.A Representativeness of the Sample

In this Appendix, we check whether participation in the uncertainty module is selective conditional on participation in the main manufacturing survey. We base our analysis on all 34,684 complete firm-quarter responses available in the main survey for the months the uncertainty module was executed. We then ask whether firm size, wave dummies, sector dummies, and interacted wave-sector dummies are able to predict participation in the uncertainty module. To this end, we run a probit regression of a participation dummy that is 1 for the 5,564 observations of the uncertainty module and zero otherwise, on these predictors and report the estimated coefficients in column (1) of Table 1.A.1. We find that there is no statistically significant selectivity with respect to wave and sector suggesting that the uncertainty sample does not misrepresent specific quarters or sectors. While firm size turns out to be significantly negative indicating that large firms are slightly underrepresented in the uncertainty module compared to the main manufacturing survey, the pseudo R-squared of 0.016 shows that this selectivity is quantitatively barely relevant. This is also reflected by a ROC curve which differs only slightly from the diagonal that indicates no discriminatory power, see Figure 1.A.1.[27]

We repeat the analysis starting from the subset of 23,486 complete firm-quarter responses available in the online part of the main survey. We thus account for the fact that some firms reply by fax and thus cannot participate in the uncertainty module which is solely implemented online. The results of an analogous probit regression are

[27] The receiver operating characteristic (ROC) visualizes the discriminatory power of a binary classifier as follows: By varying the classification threshold—here: the probability above which an observation is predicted to participate in the uncertainty module—the classifier can produce any true positive rate (type II error). The ROC curve plots the true positive rate so obtained against its corresponding false positive rate (type I error). In the case of no discriminatory power, true and false positive rates are always the same, the ROC curve equals the diagonal, and the area under the ROC curve (AUC) is 0.5. A good classifier has a ROC curve well above the diagonal and an AUC that is near the maximum of 1.0.

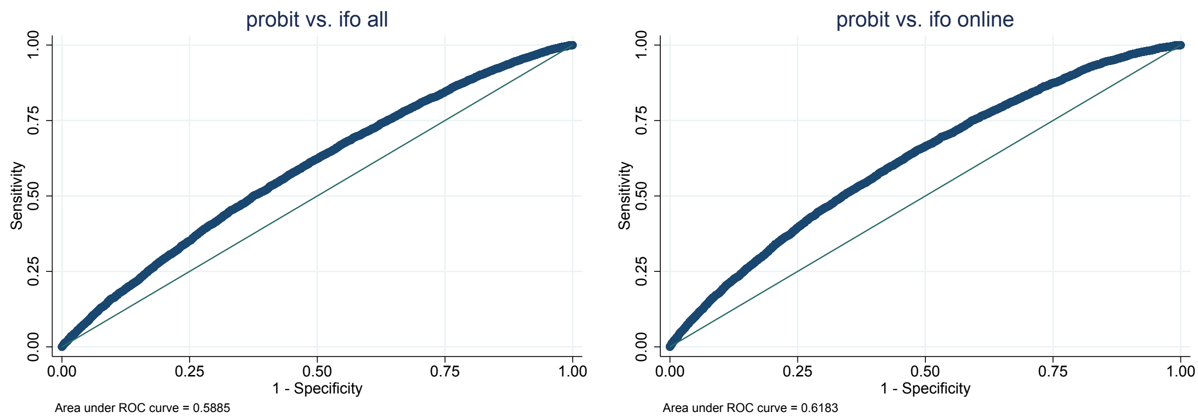
Table 1.A.1: Representativeness of special survey sample

	(1) ifo all	(2) ifo online
Log of number of employees	-0.0753***	-0.134***
	(0.0127)	(0.0139)
Dummy survey wave 1	-0.0441	0.0707
	(0.221)	(0.242)
Dummy survey wave 2	0.0647	0.235
	(0.260)	(0.289)
Dummy survey wave 3	0.248	0.452*
	(0.232)	(0.258)
Dummy survey wave 4	0.276	0.439*
	(0.217)	(0.240)
Dummy survey wave 5	0.126	0.253
	(0.204)	(0.225)
Dummy survey wave 6	0.317	0.490**
	(0.195)	(0.211)
Dummy survey wave 7	0.224	0.387*
	(0.206)	(0.225)
Dummy survey wave 8	-0.244	-0.150
	(0.247)	(0.268)
Dummy survey wave 9	0.110	0.228
	(0.235)	(0.255)
Dummy survey wave 10	0.224	0.361*
	(0.186)	(0.201)
Dummy survey wave 11	-0.0333	0.0732
	(0.179)	(0.196)
Dummy survey wave 12	0.154	0.275
	(0.182)	(0.202)
Dummy survey wave 13	0.321	0.334
	(0.218)	(0.232)
Dummy supersector 1	0.130	0.415
	(0.245)	(0.262)
Dummy supersector 2	-0.301	-0.153
	(0.271)	(0.289)
Dummy supersector 3	-0.0686	0.154
	(0.229)	(0.242)
Dummy supersector 4	-0.0697	0.0116
	(0.250)	(0.264)
Dummy supersector 5	0.136	0.335
	(0.237)	(0.250)
Dummy supersector 6	-0.129	0.000307
	(0.240)	(0.253)
Dummy supersector 7	-0.0828	0.185
	(0.250)	(0.267)
Dummy supersector 8	0.109	0.379
	(0.257)	(0.275)
Dummy supersector 9	-0.360	-0.184
	(0.232)	(0.245)
Dummy supersector 10	0.120	0.282
	(0.259)	(0.276)
Dummy supersector 11	-0.0901	0.0704
	(0.240)	(0.254)
Dummy supersector 12	-0.0935	0.0302
	(0.222)	(0.232)
Dummy supersector 13	-0.240	-0.0867
	(0.283)	(0.301)
Constant	-0.605***	-0.256
	(0.214)	(0.224)
Additional wave-supersector dummies	YES	YES
No. of observations	34684	23486
No. of firms	3428	2416
No. of parameters (excl. intercept)	196	196
Pseudo R-squared	0.016	0.030

Notes: Results from probit regressions. The dependent variable in column 1 and 2 is a dummy indicating special survey participation. In column 1 the dummy is of value zero for all other participants of the ifo survey, in column 2 the dummy of value zero for all other *online* participants. Standard errors in parentheses, clustered by firm; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

reported in column (2) of Table 1.A.1. Again, the very low pseudo R-squared suggests that selectivity is not a relevant issue for the uncertainty module. This conclusion is supported by a largely unaltered ROC curve near the non-discriminatory diagonal, see Figure 1.A.1.

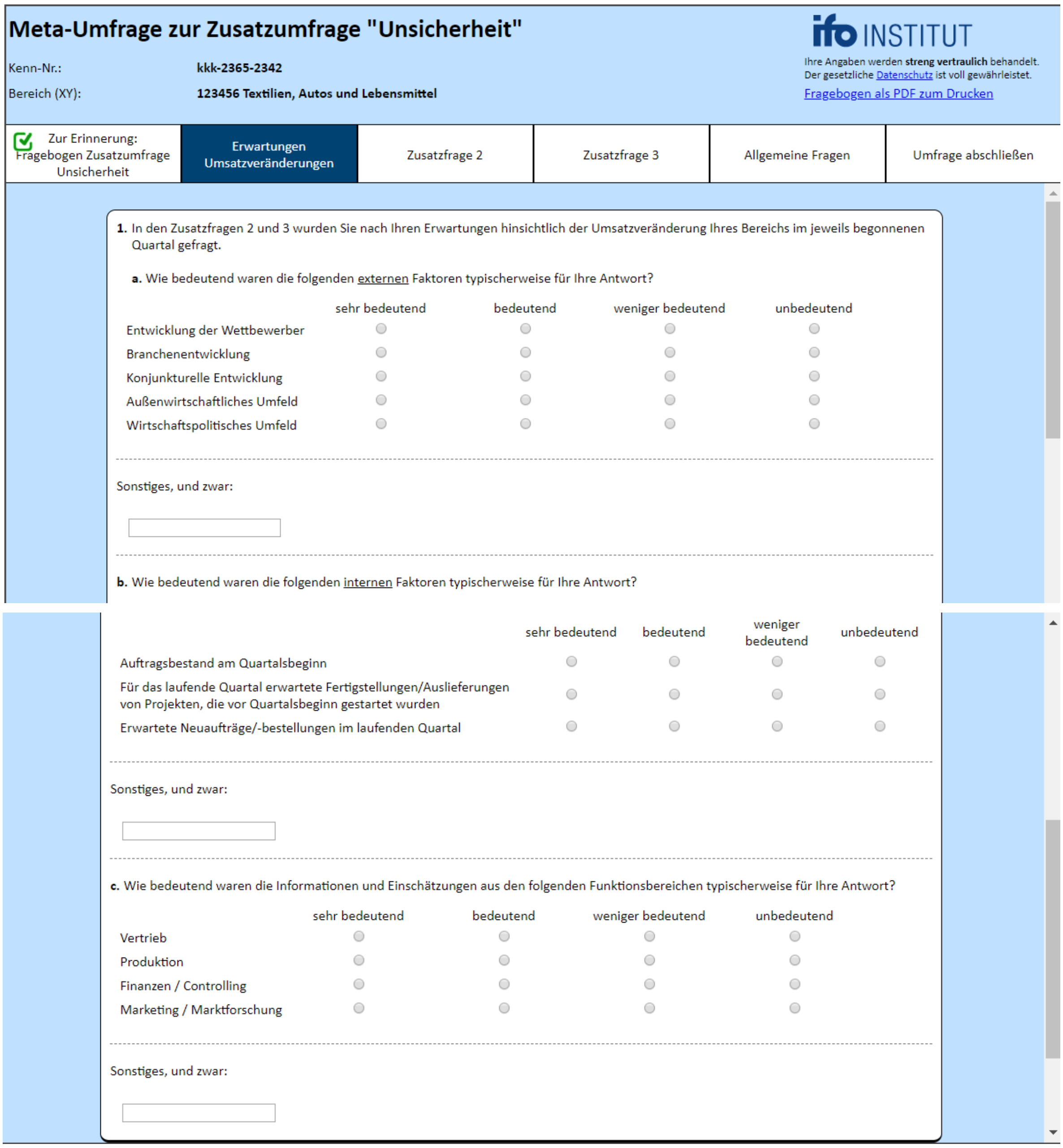
Figure 1.A.1: ROC curves for probit estimations



Note: The two plots depict ROC curves that correspond to the probit estimations in columns 1 and 2 of Table 1.A.1, respectively.

1.B Questionnaire for the One-Time Meta-Survey From Fall 2018

Figure 1.B.1: Original meta survey questionnaire in German, part 1



Meta-Umfrage zur Zusatzumfrage "Unsicherheit"

Kenn-Nr.: **kkk-2365-2342**

Bereich (XY): **123456 Textilien, Autos und Lebensmittel**

ifo INSTITUT

Ihre Angaben werden **streng vertraulich** behandelt.
Der gesetzliche Datenschutz ist voll gewährleistet.

Fragebogen als PDF zum Drucken

Zur Erinnerung: Fragebogen Zusatzumfrage Unsicherheit	Erwartungen Umsatzveränderungen	Zusatzfrage 2	Zusatzfrage 3	Allgemeine Fragen	Umfrage abschließen

1. In den Zusatzfragen 2 und 3 wurden Sie nach Ihren Erwartungen hinsichtlich der Umsatzveränderung Ihres Bereichs im jeweils begonnenen Quartal gefragt.

a. Wie bedeutend waren die folgenden externen Faktoren typischerweise für Ihre Antwort?

	sehr bedeutend	bedeutend	weniger bedeutend	unbedeutend
Entwicklung der Wettbewerber	○	○	○	○
Branchenentwicklung	○	○	○	○
Konjunkturelle Entwicklung	○	○	○	○
Außenwirtschaftliches Umfeld	○	○	○	○
Wirtschaftspolitisches Umfeld	○	○	○	○

Sonstiges, und zwar:

b. Wie bedeutend waren die folgenden internen Faktoren typischerweise für Ihre Antwort?

	sehr bedeutend	bedeutend	weniger bedeutend	unbedeutend
Auftragsbestand am Quartalsbeginn	○	○	○	○
Für das laufende Quartal erwartete Fertigstellungen/Auslieferungen von Projekten, die vor Quartalsbeginn gestartet wurden	○	○	○	○
Erwartete Neuaufträge/-bestellungen im laufenden Quartal	○	○	○	○

Sonstiges, und zwar:

c. Wie bedeutend waren die Informationen und Einschätzungen aus den folgenden Funktionsbereichen typischerweise für Ihre Antwort?

	sehr bedeutend	bedeutend	weniger bedeutend	unbedeutend
Vertrieb	○	○	○	○
Produktion	○	○	○	○
Finanzen / Controlling	○	○	○	○
Marketing / Marktforschung	○	○	○	○

Sonstiges, und zwar:

Note: Original questionnaire from ifo's one-time online meta survey on its "uncertainty module" in German, from fall 2018.

Figure 1.B.2: Original meta survey questionnaire in German, part 2

Zur Erinnerung: Fragebogen Zusatzumfrage Unsicherheit	Erwartungen Umsatzveränderungen	Zusatzfrage 2	Zusatzfrage 3	Allgemeine Fragen	Umfrage abschließen

2. Um wieviel Prozent wird sich der Umsatz in Ihrem Bereich im vierten Quartal 2018 verändern?

		weiß nicht
a) Im bestmöglichen Fall:	% (bitte ganze, positive oder negative Zahlen eingeben)	○
Im schlechtestmöglichen Fall:	% (bitte ganze, positive oder negative Zahlen eingeben)	○
b) Unter Berücksichtigung aller Chancen und Risiken erwarte ich im **vierten Quartal 2018** alles in allem eine Veränderung um:	% (bitte ganze, positive oder negative Zahlen eingeben)	○

2. In den Zusatzfragen 2 a) und b) wurden Sie gefragt, welche Umsatzveränderung Sie im jeweils begonnenen Quartal im bestmöglichen und schlechtestmöglichen Fall bzw. alles in allem für Ihren Bereich erwarten. Haben Sie bei der Beantwortung der Frage typischerweise Ergebnisse aus einer quantitativen Umsatzplanung verwendet, die ohnehin regelmäßig in Ihrem Bereich stattfindet?

- ○ ja
- ○ nein

wenn ja, wie bedeutend waren typischerweise Ergebnisse aus...

	sehr bedeutend	bedeutend	weniger bedeutend	unbedeutend
einer Szenarioanalyse um eine Basisprognose herum	○	○	○	○
einer statistischen Analyse	○	○	○	○

Sonstiges, und zwar:

3. In Zusatzfrage 2 a) wurden Sie nach der Umsatzveränderung im bestmöglichen und schlechtestmöglichen Fall gefragt. Welche der folgenden Aussagen beschreiben am ehesten Ihre Antwort?

Diese bestmöglichen und schlechtestmöglichen Fälle sind typischerweise ...

- ○ Plausible Szenarien, mit deren Eintreten wir durchaus rechnen müssen.
- ○ Mögliche Szenarien, deren Eintreten wir aber nur in Ausnahmefällen erwarten.

Sonstiges, und zwar:

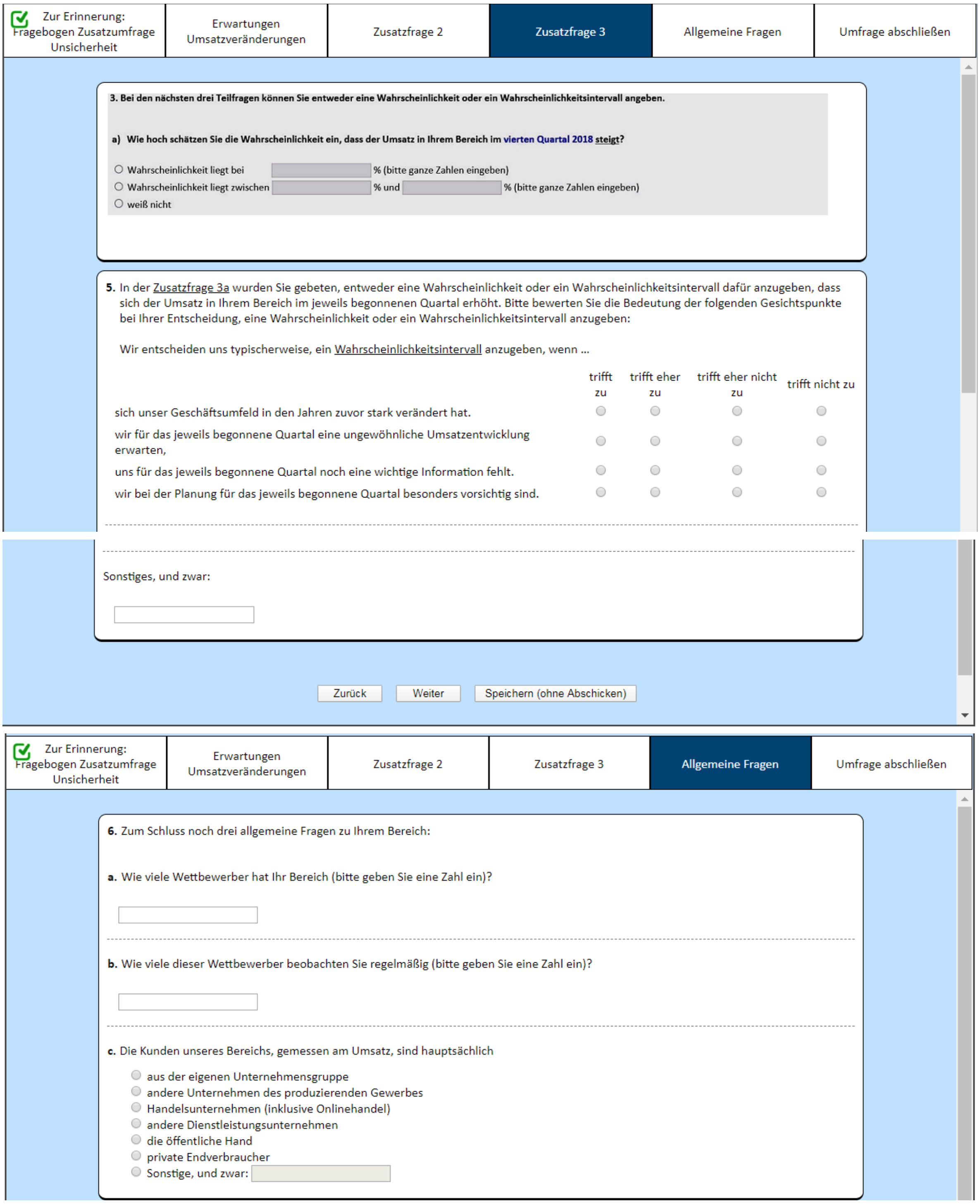
4. Wenn Sie für Zusatzfrage 2 a) die Umsatzveränderung im bestmöglichen und schlechtestmöglichen Fall ermitteln, wie bedeutend sind dabei typischerweise die nachfolgenden Gesichtspunkte für Sie?

	sehr bedeutend	bedeutend	weniger bedeutend	unbedeutend
Umsatzveränderungen in den letzten ein bis zwei Jahren	○	○	○	○
Umsatzveränderungen, die weiter als zwei Jahre zurückliegen	○	○	○	○
Überlegungen, die wir aktuell anstellen, unabhängig von der Vergangenheit	○	○	○	○
Unsere Risikoeinstellung ("Vorsichtsprinzip")	○	○	○	○
Umsatzveränderungen, die wir bei unseren Wettbewerbern beobachten	○	○	○	○

Sonstiges, und zwar:

Note: Original questionnaire from ifo's one-time online meta survey on its "uncertainty module" in German, from fall 2018.

Figure 1.B.3: Original meta survey questionnaire in German, part 3


Zur Erinnerung: Fragebogen Zusatzumfrage Unsicherheit | Erwartungen Umsatzveränderungen | Zusatzfrage 2 | Zusatzfrage 3 | Allgemeine Fragen | Umfrage abschließen

3. Bei den nächsten drei Teilfragen können Sie entweder eine Wahrscheinlichkeit oder ein Wahrscheinlichkeitsintervall angeben.

a) Wie hoch schätzen Sie die Wahrscheinlichkeit ein, dass der Umsatz in Ihrem Bereich im vierten Quartal 2018 steigt?

- Wahrscheinlichkeit liegt bei ___ % (bitte ganze Zahlen eingeben)
- Wahrscheinlichkeit liegt zwischen ___ % und ___ % (bitte ganze Zahlen eingeben)
- weiß nicht

5. In der Zusatzfrage 3a wurden Sie gebeten, entweder eine Wahrscheinlichkeit oder ein Wahrscheinlichkeitsintervall dafür anzugeben, dass sich der Umsatz in Ihrem Bereich im jeweils begonnenen Quartal erhöht. Bitte bewerten Sie die Bedeutung der folgenden Gesichtspunkte bei Ihrer Entscheidung, eine Wahrscheinlichkeit oder ein Wahrscheinlichkeitsintervall anzugeben:

Wir entscheiden uns typischerweise, ein Wahrscheinlichkeitsintervall anzugeben, wenn ...

	trifft zu	trifft eher zu	trifft eher nicht zu	trifft nicht zu
sich unser Geschäftsumfeld in den Jahren zuvor stark verändert hat.	○	○	○	○
wir für das jeweils begonnene Quartal eine ungewöhnliche Umsatzentwicklung erwarten,	○	○	○	○
uns für das jeweils begonnene Quartal noch eine wichtige Information fehlt.	○	○	○	○
wir bei der Planung für das jeweils begonnene Quartal besonders vorsichtig sind.	○	○	○	○

Sonstiges, und zwar:

Zurück | Weiter | Speichern (ohne Abschicken)

Zur Erinnerung: Fragebogen Zusatzumfrage Unsicherheit | Erwartungen Umsatzveränderungen | Zusatzfrage 2 | Zusatzfrage 3 | Allgemeine Fragen | Umfrage abschließen

6. Zum Schluss noch drei allgemeine Fragen zu Ihrem Bereich:

a. Wie viele Wettbewerber hat Ihr Bereich (bitte geben Sie eine Zahl ein)?

b. Wie viele dieser Wettbewerber beobachten Sie regelmäßig (bitte geben Sie eine Zahl ein)?

c. Die Kunden unseres Bereichs, gemessen am Umsatz, sind hauptsächlich

- aus der eigenen Unternehmensgruppe
- andere Unternehmen des produzierenden Gewerbes
- Handelsunternehmen (inklusive Onlinehandel)
- andere Dienstleistungsunternehmen
- die öffentliche Hand
- private Endverbraucher
- Sonstige, und zwar:

Note: Original questionnaire from ifo's one-time online meta survey on its "uncertainty module" in German, from fall 2018.

1.C Sample Creation

In this Section, we describe the construction of our baseline sample and also explain the number of observations from specific regressions in this paper. The numbers of observations that remain after each step are listed in Table 1.C.1. Our starting sample from 14 survey waves consists of 5,564 firm-wave observations.

Table 1.C.1: Sample creation

	firm-wave obs. in sample	firm-wave obs. excluded	firms in sample	firms excluded
Original sample	5,564		1,426	
Require response to Q1				
Response to Q1 exists	5,194	370	1,378	48
Text comment				
Wrong reference time excluded	5,095	99	1,368	10
Uncertain data quality excluded	5,067	28	1,367	1
Outliers to Q1				
Outliers in Q1 responses excluded	5,045	22	1,365	2
Number of observations by firm				
At least 5 clean responses to Q1	3,094	1,951	401	964
Outliers and inconsistencies to Q2				
Inconsistent & outlier responses to Q2 excluded	2,945	149	401	0
Require responses to Q2a				
Baseline sample span: Responses to Q2a both exist	2,762	183	400	1
Lag of forecast error exists	1,520	1,242	373	27
Lag of forecast error and lag of span exist	1,489	31	367	6
Lag of span exists	1,513	1,249	372	28
Require response to Q2b				
Baseline sample forecast: Response to Q2b exists	2,778	167	400	1
Forecast error exists	1,664	1,114	389	11
Lag of forecast error exists	949	715	292	97
Lag of forecast error, and span exist	932	17	289	3

We start by excluding 370 firm-wave observations that were lacking an answer to Q1, realized sales growth. Then we carefully read the free text comments respondents can give below each of the questions, see Figure 1.1 in the main text for the questionnaire. We exclude 99 observations for which a comment indicates that the respondent was not able to calculate sales growth rates on a quarterly basis. For example, some firms stated that they use annual growth rates instead. Moreover, we drop 28 observations for which the comment raises doubts about the validity and quality of the answer. For example, some firms were not able to state realized past growth rates and used estimates instead. Overall, we exclude 497 firm-wave observations based on missing or low-quality answers to Q1, leaving us with 5,067 firm-wave observations.

Next, we exclude 22 firm-wave observations, when the growth rate in the previous quarter elicited in Q1 lies outside the interval [-100, 100]. We set the upper bounds quite high because large (two-digit) growth rates typically appear to be deliberate responses as many text comments reveal. Firms give explanations such as "Many projects were moved into this quarter" and "Invoice of a major project." This leaves us with 5,045 firm-wave observations. After these cleaning steps we require for the firm-wave observations of a firm to remain in the sample that it have at least five clean firm-wave observations on Q1, leaving us with 3,094 firm-wave of 401 firm observations. It is this sample that we base the calculation of the trend and turbulence dummies on.

Subsequently, we exclude, respectively, outliers and inconsistencies related to Q2. Q2-outliers were excluded according to the following two criteria:

1. The best case and worst case sales growth rates elicited in Q2.a lie outside the intervals [-100; 300] and [-100; 100], respectively.
2. The expected growth rate elicited in Q2.b lies outside the interval [-100; 100].

Then we check whether respondents order the numbers in Q2 consistently, that is, as worst case < forecast < best case. We exclude firm-wave observations with the orderings worst case $\geq$ forecast $\leq$ best case or worst case $\leq$ forecast $\geq$ best case because it is unclear what the respondents had in mind with these answers. However, we kept those firm-wave observations with the inverse ordering worst case $\geq$ forecast $\geq$ best case and simply swap the worst case and best case numbers; we do this for 76 firm-wave observations. Most likely inverse orderings were not intended by the respondent and rather a simple clerical error. Altogether, we eliminate 149 firm-wave observations in this step.

In a final step, we eliminate those 183 firm-wave observations which do not have answers to Q2a, the best or worst case scenarios for sales growth, leaving us with our baseline sample of 2,762 of firm-wave observations for 400 firms ("baseline sample span"). For some other exercises, for which we do not need span observations but the answer to Q2.b, that is, the expected growth rate, we use a slightly bigger sample of 2,778 firm-wave observations ("baseline sample forecast").

Starting from the baseline sample span, for some further exercises we additionally need a lag of the forecast error, which leaves us with 1,520 firm-time observations. For the subsample of 1,489 observations, we also have the lag of span. For another exercise, we again start from the baseline sample span and require a lag of span. This subsample contains 1,513 firm-time observations.

Finally, we use the slightly larger baseline sample forecast to analyze forecast errors, which is possible for 1,664 firm-time observations. For some exercises, we use consecutive forecast errors. This reduces the sample to 1,329 firm-wave observations of which 380 are used as lagged "pre-sample" observations so that an effective sample size of 949 firm-wave observations remains. For 932 of these observations we also have span.

1.D Definition of Supersectors

Table 1.D.1 presents our definition of 14 supersectors. They are based on the 24 two-digit manufacturing sectors, which are defined by the WZ08 code of the German Statistical Office. This code is closely related to the European industry classification system NACE Rev. 2. The column with the number of observations by supersector refers to our baseline sample of 2,762 observations.

Table 1.D.1: Definition of supersectors

Supersector	Sector WZ08	Sector WZ08 name	No. of obs.
1	10, 11, 12	Food products; Beverages; Tobacco products	184
2	13, 14, 15	Textiles; Wearing apparel; Leather and related products	66
3	16, 17, 31	Wood, products of wood and cork except furniture, articles of straw and plaiting materials; Paper and paper products; Furniture	286
4	18	Printing and reproduction of recorded media	191
5	19, 20, 21	Coke and refined petroleum products; Chemicals and chemical support; Basic pharmaceutical products and pharmaceutical preparations	262
6	22	Rubber and plastic products	228
7	23	Other non-metallic mineral products	133
8	24	Basic metals	120
9	25	Fabricated metal products, except machinery and equipment	324
10	26	Computer, electronic and optical products	102
11	27	Electrical equipment	201
12	28	Machinery and equipment n.e.c.	445
13	29, 30	Motor vehicles, trailers and semi-trailers; Other transport equipment	116
14	32, 33	Other manufacturing; Repair and installation of machinery and equipment	104
All			2,762

1.E Detailed Summary Statistics

In this Appendix we report summary statistics for the answers to the questions in our survey module. Table 1.E.1 pools all firm-quarter observations and reports mean, standard deviation, and key quantiles for this pooled sample. The numbers here reflect variation both in the time series and in the cross section of firms. For Table 1.E.2, we compute, for each individual firm, the time series mean and standard deviations. The panel reports mean, standard deviation and quantiles of the cross sectional distributions of firm-level statistics. The number of observations for (functions of) forecast errors naturally drops because, in order to compute firm-level forecast errors, we need to observe the expected sales growth rate and the realized sales growth rate of a firm in two consecutive quarters.

Table 1.E.1: Summary statistics of survey answers and derived variables, pooled

Variable	N	Mean	Std. Dev.	P10	P25	P50	P75	P90
Pooled data								
Sales growth rate in the previous quarter	2762	1.71	14.69	-15	-5	2	10	15
Expected sales growth rate for the current quarter	2710	2.22	10.63	-10	0	2	5	10
Worst case sales growth rate for the current quarter	2762	-4.75	11.82	-20	-10	-2	0	5
Best case sales growth rate for the current quarter	2762	7.36	12	0	2	5	10	20
Span between worst and best case forecast	2762	12.11	9.89	3	5	10	15	25
Forecast error	1664	-.22	13.98	-15	-5	0	5	13
Forecast error from random walk model	1664	.43	17.17	-14	-5	0	5	15
Forecast error from iid process	1664	.51	10.82	-9.11	-3.21	.22	4.05	10.67
Absolute forecast error	1664	8.69	10.95	0	2	5	10	20

Notes: The cleaned sample comprises 400 firms for which we have at least five answers to question 1. Of those, we only use the firm-time observations that contain a complete answer to question 2.a, i.e. for which we can construct the span between the best and the worst case sales growth rate for the current quarter. This is our baseline sample of 2762 firm-quarter observations (see Appendix 1.C). We do not have the answer to question 2.b for all of these firm-quarter observations. We are left with 2710 firm-quarter observations with an expected sales growth rate for the current quarter. Further note, the summary statistics for all variables listed in the table above are based on the baseline sample of 2762 firm-quarter observations, except for the forecast error variables. They are also based on the sample of firms with at least five answers to question 1, but we do not require a complete answer to question 2.a in the set of firm-time observations. Instead, to compute the firms' (absolute) forecast error, we need two adjacent observations of a firm. This explains the drop in the number of observations for the (absolute) forecast error. To obtain comparability, we compute the forecast error from a random walk model and from an *iid* process, respectively, based on the same sample as for the firms' forecast errors.

Table 1.E.2: Summary statistics of survey answers and derived variables, by firm

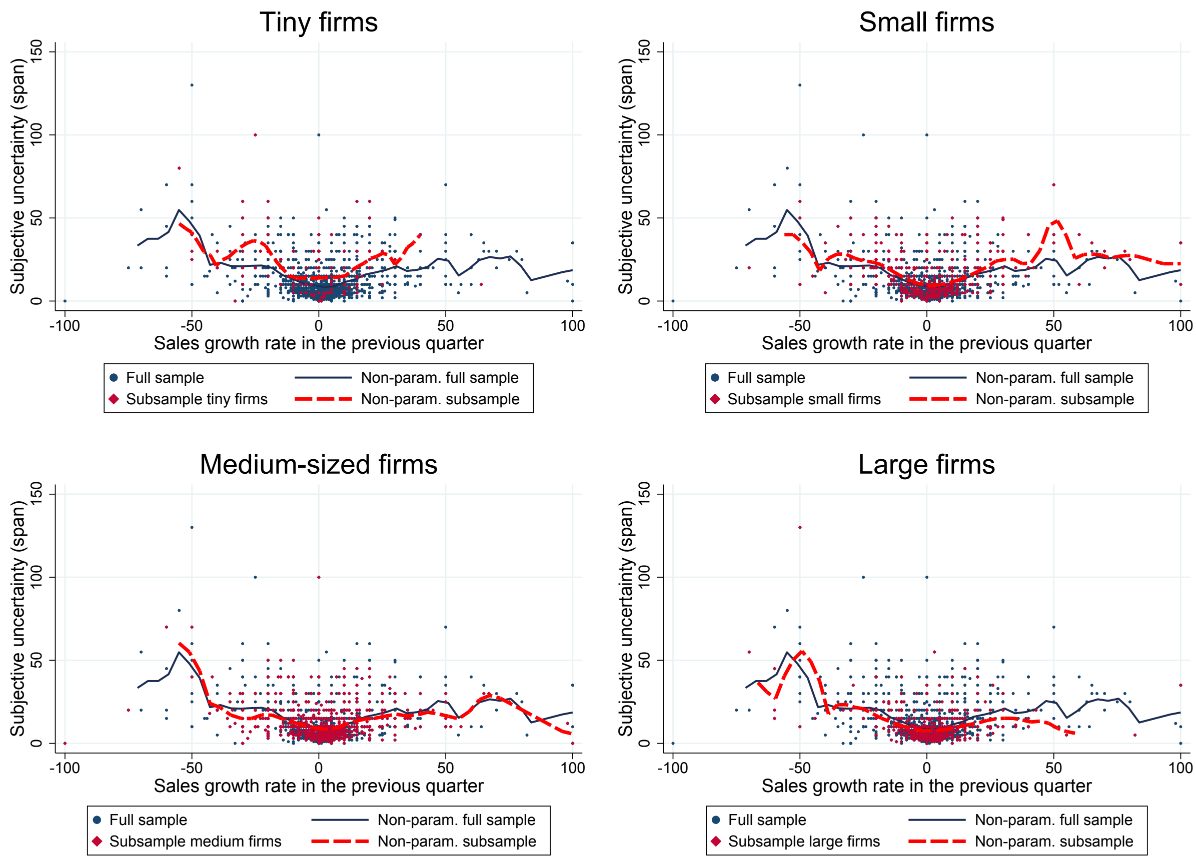
Variable	N	Mean	Std. Dev.	P10	P25	P50	P75	P90
Data by firm								
Mean by Firm: Sales growth rate in the previous quarter	400	1.74	7.87	-6.67	-1.92	1.69	5.3	10.29
Mean by Firm: Expected sales growth rate for the current quarter	399	2.61	6.57	-3.75	-.6	2.25	5	9
Mean by Firm: Worst case sales growth rate for the current quarter	400	-4.48	7.4	-13	-8.31	-3.35	-.15	2.72
Mean by Firm: Best case sales growth rate for the current quarter	400	7.87	8.02	.81	3.41	6.67	10.61	16.67
Mean by Firm: Span between worst and best case forecast	400	12.34	7.35	5.09	7.15	10.57	15.55	22.33
Mean by Firm: Forecast error	389	-.23	10.48	-10	-3.57	0	3.5	8
Mean by Firm: Forecast error from random walk model	389	.6	9.74	-8.33	-3.22	0	3.8	9.67
Mean by Firm: Forecast error from iid process	389	.55	7.67	-6.8	-2.35	.2	2.63	8.67
Mean by Firm: Absolute forecast error	389	9.44	9.55	2.25	4	7	11.67	17.57
Std. Dev. by Firm: Sales growth rate in the previous quarter	397	11.42	9.22	3.44	5.48	8.59	13.7	23.49
Std. Dev. by Firm: Expected sales growth rate for the current quarter	396	7.36	7.1	1.6	2.89	5.24	9.72	14.92
Std. Dev. by Firm: Worst case sales growth rate for the current quarter	397	8.09	7.13	2.12	3.18	6.28	10.8	16.33
Std. Dev. by Firm: Best case sales growth rate for the current quarter	397	8.13	7.78	2.16	3.43	5.87	10.31	15.52
Std. Dev. by Firm: Span between worst and best case forecast	397	5.85	5.05	2.04	2.87	4.67	7.5	10.61
Std. Dev. by Firm: Forecast error	338	10.17	9.79	2.29	4.04	7.46	12.73	20.21
Std. Dev. by Firm: Forecast error from random walk model	338	12.37	13.38	2.07	4.04	8.09	14.57	29.69
Std. Dev. by Firm: Forecast error from iid process	338	7	7.19	.71	2.3	4.51	9.9	16.42
Std. Dev. by Firm: Absolute forecast error	338	6.44	6.28	1.41	2.51	4.33	8.08	13.63

Notes: The cleaned sample comprises 400 firms for which we have at least five answers to question 1. Of those, we only use the firm-time observations that contain a complete answer to question 2.a, i.e. for which we can construct the span between the best and the worst case sales growth rate for the current quarter. This is our baseline sample of 2762 firm-quarter observations (see Appendix 1.C). We do not have the answer to question 2.b for all of these firm-quarter observations. We are left with 2710 firm-quarter observations with an expected sales growth rate for the current quarter. Moreover, some firms have frequently answered question 1, but not question 2.a. As a result, the time series mean and standard deviations are based on fewer than five observations for some firms. For three firms, we do not compute the standard deviation, since for these firms we have only one complete answer to question 2.a. This is the reason for the difference between the 400 firms for which we compute the mean, and 397 firms for which we compute the standard deviation. Further note, the summary statistics for all variables listed in the table above are based on the baseline sample of 2762 firm-quarter observations, except for the forecast error variables. They are also based on the sample of firms with at least five answers to question 1, but we do not require a complete answer to question 2.a in the set of firm-time observations. Instead, to compute the firms' (absolute) forecast error, we need two adjacent observations of a firm. This explains the drop in the number of observations for the (absolute) forecast error. To facilitate comparability, we compute the forecast error from a random walk model and from an *iid* process, respectively, based on the smaller sample of the firms' forecast errors.

1.F Uncertainty and Change by Firm Characteristics

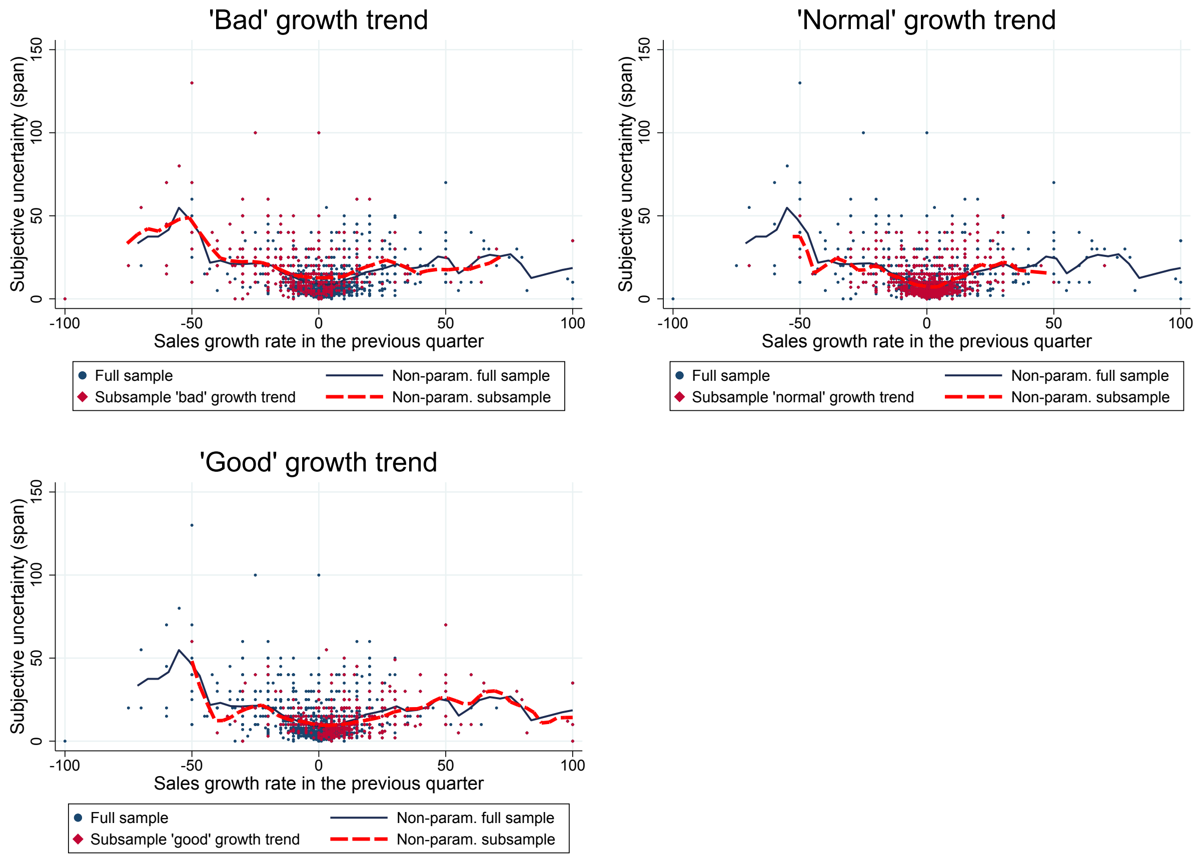
In this Section we show that the V-shaped relationship between sales growth and subjective uncertainty holds separately, and in a quantitatively similar manner, for all firm-level subgroups: the four firm size groups, the four turbulence groups, and the three growth trend groups.

Figure 1.F.1: Subjective uncertainty and past sales growth by firm size



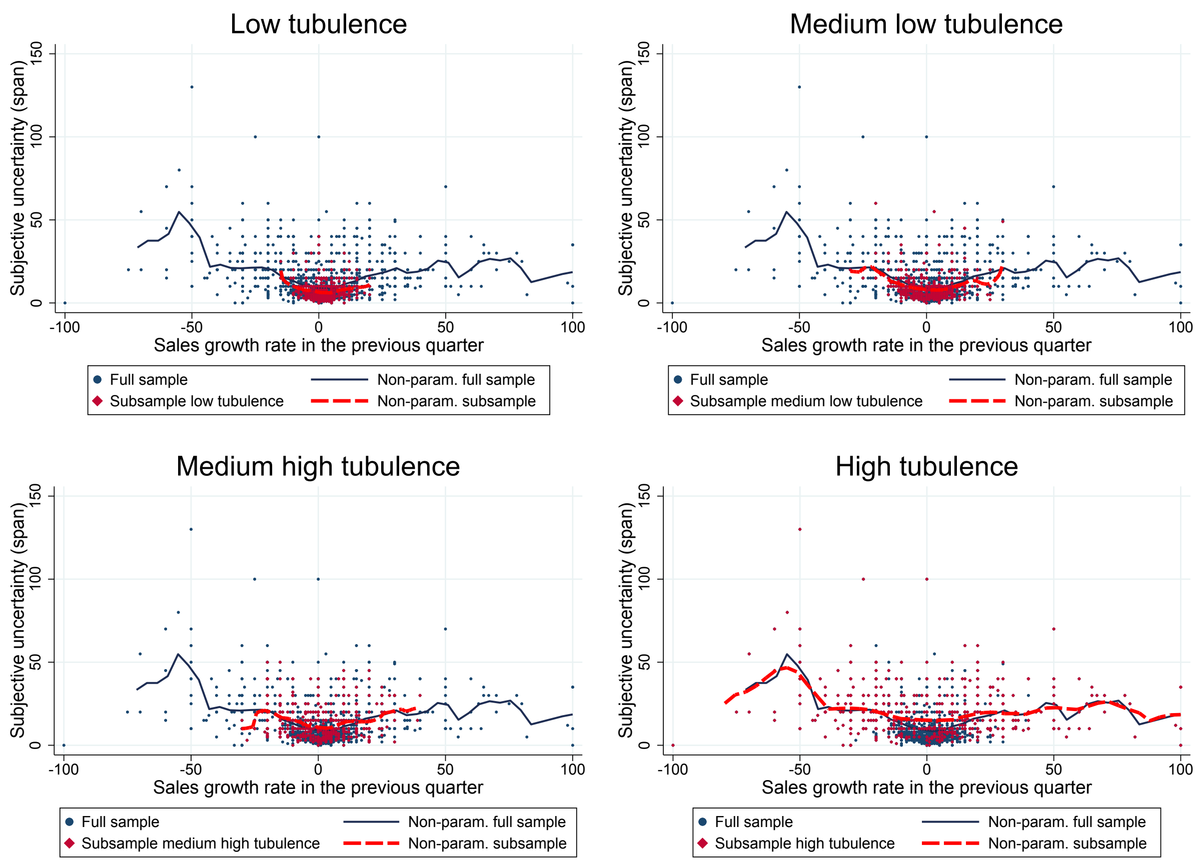
Notes: Relationship between subjective uncertainty (span) and sales growth in the previous quarter for four different firm size groups based on their number of employees: tiny, small, medium, and large firms. Scatter points and non-parametric kernel regression line of degree zero for the full sample of firm-time observations in blue, and for the subsample of the size group in red.

Figure 1.F.2: Subjective uncertainty and past sales growth by growth trend



Notes: Relationship between subjective uncertainty (span) and sales growth in the previous quarter for three different groups of firms that are defined based on their growth trend (mean of a firms' sales growth). Scatter points and non-parametric kernel regression line of degree zero for the full sample of firm-time observations in blue, and for the subsample of the trend group in red.

Figure 1.F.3: Subjective uncertainty and past sales growth by turbulence



Notes: Relationship between subjective uncertainty (span) and sales growth in the previous quarter for four different groups of firms that are defined based on their turbulence of sales growth (standard deviation of a firms' sales growth). Scatter points and non-parametric kernel regression line of degree zero for the full sample of firm-time observations in blue, and for the subsample of the turbulence group in red.

1.G Robustness of Uncertainty and Change in the Time Series

In order to test the robustness of our results, we replicate the regressions in Table 1.5 with the relationship between subjective uncertainty and past sales growth for two different samples.

In Table 1.G.1 we use a smaller sample, for which sales growth rates are not in the interval (-100,100), but in the interval (-15,15). This is the interdecile range of sales growth as depicted in table 1.E.1. The number of observations reduces from 2,762 to 2,316. Table 1.G.2 presents estimation results for a larger sample: unlike in the baseline sample, we do not require firms to have five observations with a sales growth rates, but we include all firms with at least two of such observations. This increases the sample from 2,762 to 4,120 observations. Our results are robust to these alternative sample definitions.

Table 1.G.1: Robustness sales growth in interval (-15,15): subjective uncertainty and past sales growth

	(1) POLS	(2) POLS	(3) POLS	(4) POLS	(5) POLS	(6) POLS	(7) FE	(8) POLS
Sales growth rate in the previous quarter	-0.0801***							
	(0.0269)							
Negative sales growth rate in the previous quarter		-0.582***	-0.556***	-0.456***	-0.391***	-0.308***	-0.284***	-0.284***
		(0.0593)	(0.0577)	(0.0586)	(0.0588)	(0.0570)	(0.0424)	(0.0608)
Positive sales growth rate in the previous quarter		0.383***	0.367***	0.375***	0.248***	0.265***	0.202***	0.259***
		(0.0539)	(0.0535)	(0.0538)	(0.0502)	(0.0474)	(0.0392)	(0.0478)
Dummy small firms			-2.838			-2.254		-2.524*
			(1.959)			(1.496)		(1.468)
Dummy medium sized firms			-3.999**			-2.497*		-2.739*
			(1.927)			(1.480)		(1.481)
Dummy large firms			-5.421***			-3.663**		-3.991***
			(1.963)			(1.507)		(1.537)
Dummy 'bad' sales growth trend				3.947***		2.666***		2.670***
				(0.884)		(0.839)		(0.839)
Dummy 'good' sales growth trend				0.657		-0.216		-0.650
				(0.640)		(0.641)		(0.664)
Dummy medium low turbulence					1.467***	1.262**		1.200**
					(0.558)	(0.567)		(0.608)
Dummy medium high turbulence					4.876***	4.380***		4.287***
					(0.689)	(0.693)		(0.687)
Dummy high turbulence					7.233***	6.512***		6.104***
					(0.952)	(0.934)		(0.940)
Constant	10.58***	7.543***	11.63***	6.888***	5.841***	8.388***	8.984***	7.221***
	(0.315)	(0.423)	(1.961)	(0.392)	(0.489)	(1.514)	(0.228)	(1.481)
Time-sector dummies								YES
No. of observations	2316	2316	2316	2316	2316	2316	2316	2316
No. of firms	394	394	394	394	394	394	394	394
No. of parameters (excl. intercept)	1	2	5	4	5	10	1	199
R-squared	0.0060	0.078	0.10	0.11	0.18	0.21	0.63	0.28

Notes: Results from pooled ordinary least squares (POLS) and fixed effect (FE) regressions. Piecewise linear regressions of span on past sales growth with a break at zero in columns 2 to 8, controlling for fixed firm characteristics. Sales growth rates are in the interval (-15,15). Standard errors in parentheses, clustered by firm. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 1.G.2: Robustness larger sample: subjective uncertainty and past sales growth

	(1) POLS	(2) POLS	(3) POLS	(4) POLS	(5) POLS	(6) POLS	(7) FE	(8) POLS
Sales growth rate in the previous quarter	-0.0312							
	(0.0223)							
Negative sales growth rate in the previous quarter		-0.506***	-0.480***	-0.466***	-0.400***	-0.363***	-0.290***	-0.361***
		(0.0450)	(0.0440)	(0.0475)	(0.0484)	(0.0504)	(0.0601)	(0.0514)
Positive sales growth rate in the previous quarter		0.292***	0.278***	0.294***	0.215***	0.216***	0.157***	0.215***
		(0.0253)	(0.0245)	(0.0259)	(0.0268)	(0.0258)	(0.0255)	(0.0261)
Dummy small firms			-3.443*			-2.806		-2.427
			(2.091)			(1.895)		(1.671)
Dummy medium sized firms			-5.922***			-5.018***		-4.626***
			(2.062)			(1.867)		(1.689)
Dummy large firms			-6.898***			-5.821***		-5.527***
			(2.101)			(1.890)		(1.735)
Dummy 'bad' sales growth trend				2.320***		1.469**		1.345*
				(0.740)		(0.670)		(0.695)
Dummy 'good' sales growth trend				0.452		0.00528		-0.166
				(0.534)		(0.515)		(0.510)
Dummy medium low turbulence					0.344	0.282		0.455
					(0.472)	(0.463)		(0.473)
Dummy medium high turbulence					3.326***	3.048***		3.206***
					(0.582)	(0.573)		(0.585)
Dummy high turbulence					5.395***	4.826***		4.745***
					(0.768)	(0.715)		(0.724)
Constant	12.37***	8.410***	13.93***	7.948***	7.097***	11.62***	10.14***	11.40***
	(0.292)	(0.325)	(2.077)	(0.325)	(0.378)	(1.869)	(0.375)	(2.595)
Time-sector dummies								YES
No. of observations	4120	4120	4120	4120	4120	4120	4120	4120
No. of firms	940	940	940	940	940	940	940	940
No. of parameters (excl. intercept)	1	2	5	4	5	10	1	205
R-squared	0.0023	0.20	0.23	0.21	0.24	0.26	0.61	0.31

Notes: Results from pooled ordinary least squares (POLS) and fixed effect (FE) regressions. Piecewise linear regressions of span on past sales growth with a break at zero in columns 2 to 8, controlling for fixed firm characteristics. Larger sample of firms that reported at least two realized sales growth rates. Sales growth rates are in the interval (-100,100). Standard errors in parentheses, clustered by firm. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

1.H List of Firm-Level Controls

The "**additional firm controls**" include the following variables from the ifo Business Survey:

- **Capacity utilization**: capacity utilization at the time of the survey, between 30% and 100% in pre-determined bins provided in the questionnaire; for a capacity utilization of more than 100% a free text answer is possible (in the sample, the maximum reported capacity utilization is 120%).
- **State of business**: state of business at the time of survey, coded between 0 and 100.
- **State of business dummies**: state of business at the time of survey, reported on a three-point scale. The options are "good", "satisfactory", or "bad". We define two dummies, for a good and a bad state of business.
- **Orders dummies**: order book level at the time of the survey, reported on a three-point scale. The options are "relatively high", "sufficient (for the season)", or "too low". We define two dummies, for a relatively high and a too low order book level.
- **Stock of inventory dummies**: Stock of inventories at the time of the survey, reported on a four-point scale. The options are "too big", "sufficient (for the season)", "too small", or "no stock-keeping". We define three dummies, for a too big and a too small stock of inventory, and for the case of no stock-keeping.
- **Production change dummies**: Change in production in the previous month, reported on a four-point scale. The options are "increased", "roughly unchanged", "decreased", or "no production". We define three dummies, for an increased and a decreased production, and for the case of no production.
- **Demand change dummies**: Change of the demand for a certain product of the firm in the previous month, reported on a three-point scale. The options are "improved", "unchanged", or "deteriorated" . We define two dummies, for improved and deteriorated demand.
- **Orders change dummies**: Change of the order book level in the previous month, reported on a three-point scale. The options are "increased", "roughly unchanged", or "decreased". We define two dummies, for the cases of increased and decreased order book levels.

- **Price change dummies**: Change of the price for a certain product of the firm in the previous month, reported on a three-point scale. The options are "increased", "unchanged", or "decreased". We define two dummies, for the cases of increased and decreased prices.
- **Credit appraisal dummies**: Willingness of banks to give credits to firms at the time of the survey, reported on a three-point scale. The options are "accommodating", "normal", or "restrictive". We define two dummies, for the cases of accommodating and restrictive prices.
- **Capacity utilization change dummies**: evaluation of the remaining technical capacity at the time of the survey, given the current order book level and expected new orders in the next 12 months, reported on a three-point scale. The options are "more than sufficient", "sufficient", or "not sufficient". We define two dummies, for the cases of a more than sufficient and an insufficient remaining technical capacity.
- **Constraints to production dummies**: firms report if their domestic production activity is constraint at the time of the survey. The answer options are " yes" or " no". We define one dummy for the case that domestic production constraints are prevalent.

Chapter 2

Uncertainty is More Than Risk – Survey Evidence on Knightian and Bayesian Firms*

* This chapter is based on joint work with Kai Carstensen, Rüdiger Bachmann, and Martin Schneider.

2.1 Introduction

There has been a lot of recent progress in measuring subjective beliefs of decision makers in firms. A number of surveys now elicit *quantitative* information about firms' perception of the future. Such information includes not only forecasts of firm outcomes such as sales or profits, but also measures of firm-level subjective uncertainty. However, quantitative questions about uncertainty in firm surveys usually ask for probabilities, much like those in household surveys. As a result, uncertainty is identified with risk: firms are assumed to express their views of the future in terms of probabilities, as would be natural for a textbook Bayesian decision maker.

This paper takes a new approach to eliciting firms' perception of uncertainty. We ask a simple question: what is the likelihood of a sales increase? However, rather than forcing firms to submit a single probability, we give them the option of answering with a probability *interval*. While Bayesian decision makers are thus free to report their subjective probability, others who may not feel confident to commit to a single probability can express that lack of confidence by responding with an interval – we refer to such responses as *Knightian*. Our data come from a new module in an established survey of German manufacturing firms that is known for high quality answers from top level management; we work with a five-year panel from 2013-2017.

Our main result is that Knightian perception of the future is prevalent among firms: in our five-year sample, 76% of firms choose a probability interval at least once. We further establish three sets of stylized facts about Knightian responses. First, firms report that Knightian responses are motivated by a lack of clarity about the future, and this motivation is consistent with other forecasts they make. Second, we document frequent switching between Knightian and Bayesian responses that reflects both idiosyncratic and aggregate shocks. In particular, the share of Knightian responses spikes up sharply during the Greek crisis in 2015, along with credit spreads. Finally, we show that Knightian responses do not reflect a lack of sophistication: they are also prevalent among large firms, as well as firms that use statistical analysis as a routine component of their planning process. Moreover, while we confirm existing evidence on miscalibration of firms' beliefs, we find that there is little difference between Bayesian and Knightian response on that score.

We work with data from the ifo Institute, a leading German research institute that is heavily involved in business cycle forecasting. The ifo Business Survey was introduced in 1949 and now serves as a key input to the EU-harmonized business survey. In 2012, we proposed a new quarterly survey module on uncertainty. After initial testing in 2012, the module has been in the field since early 2013, with participation stable at 300-400 firms per wave. In addition, ifo has occasionally performed meta-surveys to assess data quality and query firms for their motivation and methods when answering survey questions. We thus know that the responder within a firm changes infrequently and typically uses the results from routine quantitative planning procedures when filling out the questionnaire. We also draw on a 2018 meta-survey on uncertainty that deals specifically with Knightian responses.

We characterize responses both at the extensive margin – Bayesian or Knightian – and at the intensive margin, the actual probability forecasts. At the extensive margin, Knightian responses are a tool used by managers to express uncertainty in particular quarters; they do not reflect a constant trait of a firm. Indeed, the share of Knightian responses in a given quarter fluctuates between 20% and 35% over our sample, with a mean of 28%. It is much smaller than the 76% share of *ever-Knightian* firms: those that give a Knightian response at least once in our sample. The panel dimension of our data is thus key to assessing the propensity to respond in a Knightian fashion. Switching between responses is such that firms occasionally enter persistent Knightian spells: the typical firm switches to a Knightian response roughly once every 5 quarters, and it remains Knightian for 1.8 quarters on average; the probability of remaining Knightian is a little less than one half.

The distribution of both probabilities in Bayesian responses and probability intervals in Knightian responses shows large heterogeneity over time and across firms. Bayesian responses are close to uniformly distributed across the interval zero one – as one might expect when managers respond to high frequency information about their environment. The average probability interval in a Knightian response has a maximum probability that is also uniform, and an average width of 20pp. Average width varies little with the location of the interval, which we measure by the midpoint probability. This result shows that Knightian behavior is prevalent even among managers who are optimistic about sales growth. At the same time, the average Knightian interval has a midpoint about 10pp below the average Bayesian point probability. In this sense, Knightian responses are unconditionally correlated with pessimism about the future.

Why do managers give Knightian responses? We answer this question in two steps. We first explore firms' self-assessment: the fall 2018 meta-survey asks firms to indicate the importance of different candidate reasons for Knightian responses. The most important reason firms report is that business is expected to be, or has recently been "unusual". Remarkably, these reasons are cited equally frequently by *always-Bayesian* firms that have never chosen a probability in our sample. The propensity to engage in Knightian reasoning is thus likely to be positive even among this group. Two other candidate reasons are a lack of information and cautious planning. Both are considered less important by the average firm – they are cited by only 40% – but are emphasized especially by *often-Knightian* firms – those with a particularly high in-sample share of Knightian responses.

If Knightian responses are part of a thought-out planning process, as firms' self-assessment suggests, they should be systematically related to other numbers used in planning. Our second step in exploring managers' motivation thus draws on another part of the survey that asks firms for a forecast of one-quarter-ahead sales growth, along with best and worst case scenarios. We show that Knightian responses are more frequent when their forecast is close to zero and when the best and worst case scenarios bracket zero – that is, when one would expect a lack of clarity about the event "sales increase". At the same time, the share of Knightian responses is higher when the manager's outlook on the future is more pessimistic, as measured for example by its forecast. This is also plausible if managers become more cautious in bad times. We conclude that firms' self-assessment in the 2018 meta-survey fits well with their actual forecasting practice observed in earlier years.

Are Knightian responses given by unsophisticated decision-makers who do not understand probabilities? Or do they come from managers who are good with numbers, but simply choose to express uncertainty differently? We again provide a two-step answer: we begin with self-assessment and then study forecasting performance. The meta-survey asks firms a number of questions about their planning process. The main takeaway is that there is no relationship between the frequency of Knightian responses and firms' planning tools. In particular, roughly equal shares of ever-Knightian and always-Bayesian firms engage in (i) routine quantitative planning (about 80%), (ii) statistical analysis (57%) and (iii) scenario analysis (67%). The latter is a popular business planning approach that explores scenarios around a baseline forecast, without necessarily attaching probabilities; a key example is stress testing in banks.

What about actual forecasting performance? We show that Knightian responses are about as bad as Bayesian responses in predicting the event of a sales increase. A standard performance measure for Bayesian forecasters is the difference between the probability forecast of an event and its conditional empirical frequency. Our Bayesian responses reflect the familiar property of "miscalibration due to overprecision": managers who submit small (large) probabilities underpredict (overpredict) the occurrence of the event. Knightian responses share this property: Knightian midpoint probabilities are miscalibrated to essentially the same extent as Bayesian responses. Since Knightian responses consist of intervals, we also consider a second measure of miscalibration: a Knightian forecasters is well-calibrated if the conditional empirical frequency of the event falls inside the interval. According to this weaker criterion, only a moderate share of Knightian responses that provide fairly high intervals are in fact well calibrated.

How does Knightian reasoning vary over time? We show there is both a sizeable aggregate component and a large idiosyncratic component. We define the aggregate component as the quarterly Knightian response share. Its movement can be divided into three phases. The Knightian share declines during the recovery from the European crisis in 2013 and late 2014, then spikes up sharply during the Greek crisis in the first half of 2015, and finally declines again as the recovery continues. In fact, the Knightian share closely tracks movements in the spread between Greek and German government bonds, a proxy for macroeconomic risk in the Eurozone during this time period. This finding lines up well with macro-finance models of Knightian uncertainty that predict joint movements in perceived Knightian uncertainty and measured risk premia, such as those present in credit spreads.[1]

Idiosyncratic variation in Knightian uncertainty depends on firm characteristics in a limited way. We show that it is quite difficult to predict when firms switch from Bayesian to Knightian responses using fixed characteristics. Regardless of whether firms are large or small and what sector they are in, they enter a Knightian spell about once every five quarters. This result underscores that Knightian responses do not reflect a fixed trait of a firm, but are instead a tool used by its managers at certain times when they lack clarity about the future. At the same time, we do see systematic differences across firms in the duration of Knightian spells. We show in particular that small firms, firms who do not export and firms that grow more slowly experience more persistent Knightian spells, and hence give Knightian responses overall more frequently. This finding squares well with our finding on motivation above: often-Knightian firms cite "caution" as a particularly important reason for Knightian responses.

The global nature of the macro event in our sample – the Greek crisis – creates an interesting connection between idiosyncratic and aggregate dynamics. Indeed, we would expect that small firms and in particular those who do not export should be less affected by news about Greece than large exporting firms. We find that this is indeed the case: we show in an accounting exercise that the increase of the Knightian response share in 2015 is driven mostly by firms *entering* Knightian spells. Moreover, the Knightian share spikes much more strongly in 2015 among large firms as well as exporters, two groups that unconditionally exhibit below average Knightian shares.

[1] Knightian uncertainty has been found to help account for asset pricing (Epstein and Wang, 1994), banking crises (Caballero and Simsek, 2013), business cycles (Ilut and Schneider, 2014) and the joint determination of output, firm financing and risk premia (Bianchi et al., 2017).

By contrast, the Knightian share for small firms rises with a delay and peaks only in 2016. In fact, it comoves much more strongly with the spread on investment grade debt – a measure of funding cost for firms – than with the spread between Greek and German bonds. In line with our general theme, Knightian responses are a tool to express uncertainty and hence respond to what source of uncertainty firms care about most.

Our paper is related to several strands of literature. First, we contribute to the growing body of work on quantitative (as opposed to categorical) survey measures of uncertainty. Following the early contribution of Juster (1966), most of the literature has focused on households. There are now many household surveys that measure uncertainty, see for example papers based on the Health and Retirement Study (Juster and Suzman, 1995; Hurd and McGarry, 2002), the Bank of Italy's Survey of Household Income and Wealth (Guiso et al., 1992, 2002), the Survey of Economic Expectations (Dominitz and Manski, 1997), the Michigan Survey of Consumers (Dominitz and Manski, 2004) and the New York Fed's Survey of Consumer Expectations (Armantier et al., 2015). However, most uncertainty-related questions attempt to elicit probabilistic beliefs.

A smaller literature studies survey measures of uncertainty in firms. Guiso and Parigi (1999) pioneered this line of research using data from the Bank of Italy (see also Bontempi et al., 2010); their focus was on the effect of sales growth uncertainty on investment. Ben-David et al. (2013) and Gennaioli et al. (2016) investigate executives' stock return expectations while Coibion et al. (2018b) are interested in uncertainty perceived about aggregate outcomes. Bloom et al. (2017) designed a new survey of US firms that measures sales growth uncertainty (see also Altig et al., 2019). All of these studies identify uncertainty with risk: they construct measures of uncertainty from elicited probabilities. Our earlier paper Bachmann et al. (2018) proposed an alternative measure based on best and worst case scenario forecasts that makes sense for both Bayesian and Knightian respondents. What is new in the present paper is that we use probability forecasts and explicitly distinguish Bayesian from Knightian responses.

Frank Knight introduced the distinction between risk and what is now called Knightian uncertainty (or "ambiguity") in his 1921 book, "Risk, Uncertainty, and Profit". A decision-theoretic literature on ambiguity began with Ellsberg (1961), who showed that the distinction between risk and ambiguity is behaviorally meaningful. Gilboa and Schmeidler (1989) proposed a popular axiomatic model of decision making that represents utility using a convex set of probabilities. There have been some attempts to measure attitude towards Knightian uncertainty in the lab or in surveys using a revealed preference approach closely tied to theory – typically subjects are asked how they rank bets on uncertain events (for example, Asparouhova et al. 2015, Dimmock et al. 2016). In this paper, we instead directly ask survey respondents to provide probability intervals or single probabilities. We therefore do not take a stand on a particular model of decision making – what we are interested in is only in whether people think in terms of probabilities or not.

Our approach is thus closer to a small literature that elicits imprecise probabilities in household surveys, pioneered by Manski and Molinari (2010). The typical survey design uses a multi-part question: after first asking for the probability of an event, a follow up question allows respondents who are not sure about their answer to specify a probability interval. This approach has been used to measure uncertainty about schooling (Giustinelli and Pavoni, 2017), health outcomes (Giustinelli et al., 2019) or households' financial situation (Delavande et al., 2019). Our survey design is different since we ask every respondent directly about a probability or probability interval. Moreover, our data set is unique in that it comes from a business survey and consists of a multi-year panel of probability interval responses that we can use to study the dynamics of Knightian responses and their relationship to macroeconomic events.

The rest of the paper is structured as follows. Section 2.2 introduces our data and provides a first set of summary statistics about Knightian responses. Section 2.3 reports results from firms' self-assessment that speak to both motivation and sophistication and compares them to their forecast and forecasting performance. Finally, Section 2.4 studies the aggregate and idiosyncratic movements in Knightian responses.

2.2 Data

Our data come from an "uncertainty module" for manufacturing firms in the ifo Business Survey, designed in 2012 and first described in Bachmann et al. (2018).[2] The main ifo survey has been run in Germany since 1949; it provides input for a leading indicator of the German business cycle, the ifo Business Climate Index. Moreover, the ifo Business Survey elicits data that feed into the European Economic Sentiment Indicator published by the European Commission. The uncertainty module is administered at the beginning of every quarter. In addition, in fall 2018, a one-time meta-survey asked firms how they collect information and arrive at the views expressed in our uncertainty module.

[2] The raw data can be found under IBS-IND (2017).

The uncertainty module has been in the field every quarter since 2013, the current sample consists of 19 survey waves spanning 2013:Q2 through 2017:Q4. Participation has been stable at 300-400 firms per wave; more than 500 firms participated in the meta-survey. Throughout this paper, "firm" refers to either a stand-alone business or a division of a large conglomerate. Survey questions ask about uncertainty in sales growth. The German term used in the questionnaire, “Umsatz”, is a well-defined technical term in profit and loss accounting, translated into English as “sales” or “total revenue.” It is commonly used as an accounting statistic at the levels of both a division and an entire firm.

Our earlier paper (Bachmann et al., 2018) contains more detailed information about survey design, representativeness and quality of the responses. We emphasize in particular that (i) the identity of the responder within a given firm changes infrequently, (ii) the typical responder holds a leading position in their firm, and (iii) responses typically incorporate results from routine quantitative planning. These findings are robust to firm size – they hold, in particular, also for large firms (or divisions).[3] Finally, questions in the main survey that ask about realized outcomes (such as production) explicitly ask firms to ignore seasonal fluctuations. Consistent with this, we observe only negligible seasonal effects in our data.

2.2.1 The Subjective Likelihood of a Sales Increase

Figure 2.1 displays an excerpt from the questionnaire for April 2014 in the original German. In English, the question reads:

3. You can either answer with a probability or a probability interval:
(a) how do you assess the probability (in percentage terms) that your sales will increase in the second quarter of 2014?

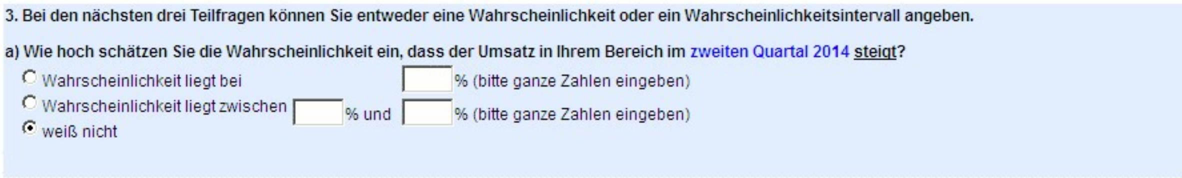
- *Probability is ____% (please insert integers)*
- *Probability lies between _____% and ____% (please insert integers)*
- *don't know*

Parts (b) and (c) of the question are structured and phrased identically, except that the word “increase” is replaced by “stay the same” and “decrease”, respectively. The questionnaire form contains boxes for respondents to provide their numerical answers. It also features a third option “don't know” (“weiss nicht” in German); it is checked in

[3] The median firm in our sample has 100 employees, while the 75th percentile is at 250.

the screenshot. A final box underneath part (c) allows firms to provide free-form text comments ("Anmerkungen").

Figure 2.1: Original survey questionnaire in German


3. Bei den nächsten drei Teilfragen können Sie entweder eine Wahrscheinlichkeit oder ein Wahrscheinlichkeitsintervall angeben.

a) Wie hoch schätzen Sie die Wahrscheinlichkeit ein, dass der Umsatz in Ihrem Bereich im zweiten Quartal 2014 steigt?

- Wahrscheinlichkeit liegt bei ____ % (bitte ganze Zahlen eingeben)
- Wahrscheinlichkeit liegt zwischen ____ % und ____ % (bitte ganze Zahlen eingeben)
- weiß nicht

Notes: Original questionnaire from ifo's online module on subjective uncertainty in German; screenshot from April 2014.

To clarify the timing, consider a firm responding in early April 2014, that is, at the beginning of 2014:Q2. The probability, or probability interval, we ask for is then about the percentage change in sales between 2014:Q1 and 2014:Q2. In other words, we elicit subjective beliefs about the current quarter at the beginning of that quarter, at a point in time when sales of the previous quarter are already known.

Our baseline sample consists of 569 firms and 4646 firm-quarter observations from 19 quarters. It is derived from the raw data in two steps. First, we check for consistency of answers, such as whether the upper bound of the probability interval is above its lower bound and percentages are between 0 and 100. We also use text comments to drop firms unwilling or unable to provide sensible numerical answers. Second, some of our analysis requires that an individual firm shows up in the panel sufficiently often. We thus restrict attention to firms that respond at least five times.

2.2.2 Summary Statistics: The Prevalence of Knightian Responses

We divide responses about the likelihood of a sales increases into three groups: Bayesian, Knightian and Certain. Our survey asks about a particular event, a sales increase. Discussing differences in attitudes towards uncertainty makes sense only for those firms that actually perceive uncertainty about the event. We thus separately consider *certain* responses that are equal to zero or one. The remaining *uncertain* responses are then divided into *Bayesian* responses that consist of a single probability and *Knightian* responses that consist of a probability interval. The *Knightian share* is the ratio of Knightian to uncertain responses.

In our pooled sample of over 4500 firm-quarter observations, the Knightian share among uncertain firms is 28%. Indeed, the 82% uncertain responses consist of 59% Bayesian and 23% Knightian responses. The Knightian share varies over time, but quarterly shares remain between 20% and 35% – we return to this variation in Section

2.4.2 below. The share of certain responses in the pooled sample is 18%. Certainty is more prevalent when the outlook for sales is bad: in about 13% of firm quarters, management believed that there is no chance of a sales increase, whereas in 5% of firm quarters they were sure an increase would occur.

Is a Knightian response a trait of a small share of firms, or is it instead a choice sometimes made in most firms? The panel dimension of our data allows us to measure how many firms have *ever* made use of the probability interval option in our sample. We define an *ever-Knightian* firm as one that provides a Knightian response at least once. An *always-Bayesian* firm never gives a Knightian response. For some of the results below we further split ever-Knightians into two subsets by the frequency of Knightian responses: *sometimes-Knightians* are ever-Knightians with a frequency less than or equal to the median – which is equal to one third –, whereas *often-Knightians* are those with a frequency above the median.

For the 422 firms in our sample that provided at least five responses, the share of ever-Knightian firms is 76%. In other words, the overwhelming majority of firms makes use of the probability interval option at least once. The large difference between the share of ever-Knightian firms and the quarterly Knightian response share underscores the importance of the panel dimension to assess the incidence of Knightian attitudes: any single snapshot quarter would severely underestimate the propensity to give Knightian responses. Since the identity of the decision maker who fills out the questionnaire changes infrequently, we can conclude that most decision makers in firms rely on Knightian responses to express uncertainty.

The discrepancy between shares of ever-Knightian firms and Knightian responses also implies that there must be substantial switching between responses – firms switch back and forth between the two modes of expressing uncertainty. Table 2.1 describes churn with a simple empirical transition matrix. Here we restrict attention to the subsample of firm-quarters such that we observe the firm to be uncertain also in the subsequent quarter. Unconditional moments from this subsample are essentially the same as for the main sample, and the transition to certainty is close to independent.

The key property of the transition matrix is that firms occasionally enter persistent *Knightian spells*. Indeed, the probability of switching from a Bayesian to a Knightian response is .19; it is below the unconditional probability of a Knightian response under the stationary distribution of .26. At the same time, the probability of remaining Knightian for one more period is .45. Under the stationary distribution, firms spend on average one out of every four quarters as Knightians, the typical firm enters a Knightian spell about once every five quarters, and the duration of the typical spell is 1.8 quarters.

Table 2.1: Transition matrix for Knightian and Bayesian responses

	Knightian in t	Bayesian in t
Knightian in t-1	0.45 (0.03)	0.55 (0.03)
Bayesian in t-1	0.19 (0.01)	0.81 (0.01)

Notes: Transition matrix for Knightian and Bayesian responses between two subsequent quarters, based on 1790 firm-time observations.

Table 2.2 provides summary statistics of probabilities submitted by firms. The distribution of probabilities in Bayesian responses is basically uniform, with a mean of .5. For Knightian responses, we use the midpoint of the probability interval as a measure of location. The average interval is centered around .39. The distribution of midpoints is still fairly close to uniform, although it is shifted to the left: the typical Knightian interval reflects more pessimism than the typical (degenerate) Bayesian interval.

Table 2.2: Summary statistics for Bayesian and Knightian probabilities

		Mean	SE(Mean)	P10	P25	P50	P75	P90
Bayesian	probability	0.50	0.01	0.10	0.25	0.50	0.75	0.90
Knightian	midpoint probability	0.39	0.01	0.05	0.13	0.35	0.60	0.80
	minimum probability	0.30	0.01	0.00	0.05	0.25	0.50	0.70
	maximum probability	0.47	0.01	0.10	0.20	0.50	0.70	0.90

Notes: We define the Knightian midpoint probability as the midpoint between the upper and lower bound of the probability interval of a Knightian response. We label these bounds minimum and maximum probability.

The distribution of the maximum probability in Knightian responses, that is, the upper bound of the probability interval, is very similar to that of the Bayesian probabilities. By contrast, the density of the minimum probabilities is shifted to the left by roughly 20pp; the mean width of a probability interval is 17pp. At the intensive margin, that is, interval width, uncertainty expressed via Knightian responses is therefore on average similar regardless of the location of the interval, as captured for example by the midpoint.

2.3 Why Knightian Responses?

In this section, we characterize the circumstances under which firms choose Knightian responses. We begin with firms' self-assessment of their planning process as well as their choice of response when uncertain. We then check how Knightian responses relate to other statistics relevant for planning elicited by the survey, including forecasts and best and worst case scenarios. Finally, we compare the calibration of Knightian and Bayesian responses.

The main takeaway is that there is no relationship between the frequency of Knightian responses and firms' planning tools: Knightian responses occur also in firms that have a sophisticated sales planning procedure in place. Knightian responses are, however, prevalent in firms where business is expected to be, or has recently been "unusual". Knightian responses also correspond in meaningful ways to other relevant planning statistics: they are more frequent when firms' sales forecast is close to zero, and when their best and worst case sales growth scenarios bracket zero growth. Finally, we find that Bayesian and Knightian responses reflect similarly miscalibrated beliefs.

2.3.1 How Firms View Their Survey Responses

Results in this section rely on the one-time meta-survey conducted in the fall of 2018. We can match 221 of these firms to respondents of earlier waves; due to item nonresponse the usable number of observations varies slightly across questions. The questionnaire in the original German is shown in Appendix 2.A. We describe the relevant questions in the text below.

Quantitative Planning Tools and Knightian Responses. We first check whether the frequency of Knightian responses is explained by the nature of firms' planning process. For example, do some firms provide Knightian responses because they take a less sophisticated or more informal approach to planning? We use a meta-survey question that elicits what type of information firms use when they fill out our survey questions about forecasting in the quarterly questionnaire. On average, 81% of firms state that they are guided by numbers the firm has already developed in house as part of a "regular quantitative planning process". Moreover, that share is remarkably stable across firms with different Knightian response shares: it is 78% for always-Bayesians, 82% for sometimes-Knightians, and 82% for often-Knightians.

We further explore whether the similarity between firms with different Knightian response shares extends to the use of specific planning tools. The meta-survey asks those firms that report the use of quantitative planning tools follow-up questions about the importance of prominent approaches. In particular, the question elicits the importance of statistical analysis. It also asks about the use of scenario analysis, that is, thinking about the future in terms of a few concrete, and possibly fairly detailed scenarios without necessarily attaching probabilities. A well-known example of scenario analysis is bank stress testing: banks are asked to forecast losses given a detailed set of contingencies, but they are not asked to assign probabilities to those contingencies.

Concretely, the follow-up question is:

For the typical survey answer, how important were results from

(i) a scenario analysis around a baseline forecast

(ii) statistical analysis

(iii) other (please name).

For each of the options (i)-(iii), firms were asked to rate importance on a four point scale: not important, less important, important or very important. Firms who chose case (iii) were further given the option to list an alternative approach as a free text comment. Results are presented in Fig. 2.1.

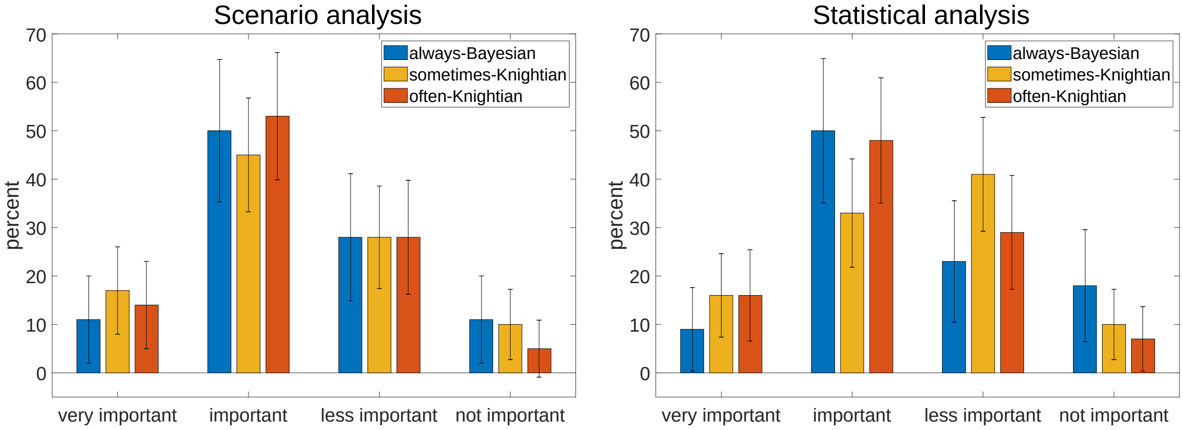
Scenario analysis is very important or important for almost a two thirds majority of all firms, as shown in the left panel of the figure. This is in line with previous findings that scenario analysis is common in German businesses.[4] Again, distinguishing between different subgroups of firms reveals remarkable similarity: scenario analysis is at least important for 61% of always-Bayesians, 62% of sometimes-Knightians, and 67% of often-Knightians.

The results for statistical analysis are shown in the right panel of Fig. 2.1. On average 57% of all firms indicate that statistical analysis is important or very important for their planning process. Again, heterogeneity between always-Bayesian and ever-Knightian firms is small. Statistical analysis is considered to be at least important by 59% of always-Bayesians, 49% of sometimes-Knightians and 64% of often-Knightians. We conclude that differences in planning technology do not push firms towards either a probability value or a probability interval. In particular, we do not find evidence for the view that the choice of a probability interval simply reflects lack of sophistication in firms' quantitative planning.

Motivation for Knightian Responses. Why would a firm prefer a probability interval over a single probability value when expressing uncertainty about a sales increase? The meta-survey includes the following direct question:

[4] Mietzner (2009) provides an overview of the literature on strategic planning in German firms. In many industries, the majority of firms engage in some sort of scenario analysis.

Figure 2.1: Importance of scenario analysis and statistical analysis



Notes: Data from fall 2018 meta-survey. Multiple choice questions elicit importance of scenario analysis (result in left panel) and statistical analysis (right panel); candidate answers are shown along horizontal axis. Height of colored bars measures share of firms that chose each importance level, out of total of all firms of the same type. Colors indicate firm types: *Always-Bayesian* = never gave a Knightian response (used a nondegenerate probability interval) in the 2013-17 sample; *Ever-Knightian* = gave a Knightian response at least once; *Sometimes-Knightian* = ever-Knightian that gave a Knightian response less or equally often as the median ever-Knightian; *often-Knightian* = ever-Knightian that gave a Knightian response more often than the median firm ever-Knightian. Gray whiskers indicate ± 1.96 standard error bands.

We choose a probability interval when...

...our business environment has changed a lot in recent years.

...we expect an unusual sales development in the current quarter.

...we are missing an important piece of information.

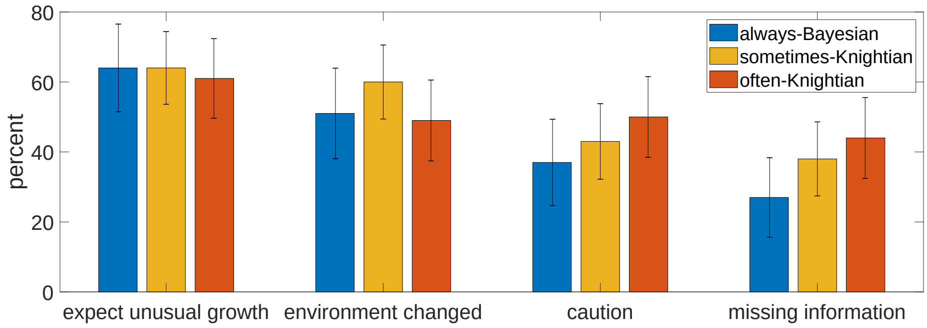
...we are particularly cautious for the current quarter.

For each candidate answer firms may state “applies”, “applies somewhat”, “does not really apply”, and “does not apply at all”. Firms can thus provide multiple reasons for choosing Knightian responses.

Fig. 2.2 reports shares of firms that state “applies” or “applies somewhat”, again by type of firm. For each candidate answer, we present three bars, one for each of the subgroups that reflect frequency of Knightian responses. One interesting takeaway here is that even firms in our always-Bayesian group engage with the question and provide motivation for a Knightian response, even though at the time of the meta-survey they had never actually provided one. This result suggests that the share of firms that contemplates Knightian responses, and hence views them as a useful tool to express uncertainty is even larger than the 76% of ever-Knightian firms.

What specifically motivates firms to give Knightian responses? To create the figure, we have ordered answers by importance. Nearly two thirds of all firms choose a prob-

Figure 2.2: Motivation for stating a probability interval



Notes: Data from fall 2018 meta-survey. Question elicits importance of candidate motivations for Knightian responses shown along the horizontal axis. Height of colored bars measures share of firms that labeled the candidate motivation "very important" or "important", out of total number firms of the same type. Colors indicate firm types defined as in Figure 2.1. Gray whiskers indicate ± 1.96 standard error bands.

ability interval when they expect an unusual sales development in the future and there is essentially no difference across groups. The second most important reason for responding in a Knightian fashion is large changes in the business environment, cited by 51% of always-Bayesians, 49% of often-Knightians and 60% of sometimes-Knightians. The latter may assign greater importance to this motive because large changes happen infrequently. Firms that use a Knightian response mostly as a reaction to exceptional changes naturally end up in the sometimes-Knightian group.

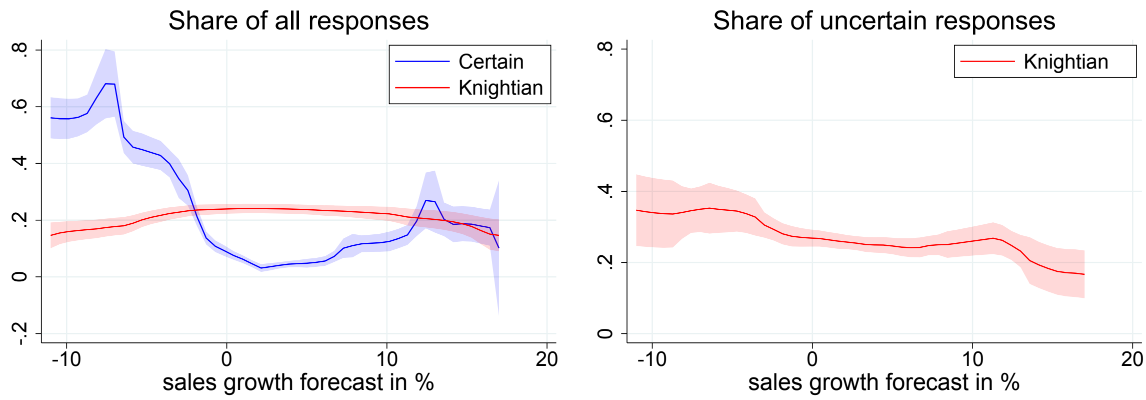
Caution is cited as a reason for a Knightian response by about 40% of all firms. This is an important result since it indicates that Knightian responses can reflect the firm's objective function, and not only its views of the variable "sales increase" that is being predicted. Interestingly, this reason is mentioned more frequently by the often-Knightian group of firms than by the other groups. The least important motive is lack of an important piece of information. However, it is cited by 44% of often-Knightian firms, again much more so than by other firms. We conclude that there is some evidence of heterogeneous motives: firms who give Knightian responses more often tend to do so more out of caution or a lack of information.

2.3.2 Relationship With Other Planning Output

Firms' self-assessment in the previous section suggested that Knightian responses represent an expression of uncertainty that reflects mainly an unusual business environment and, to a lesser extent, caution. We now investigate whether these motives are corroborated by the relationship between answers to our main question and other information we have about firms' beliefs. In particular, if beliefs about the environment matter, then we would expect that there are more Knightian responses when firms' forecasts suggest that the event "sales increase" is more uncertain. Moreover, if we postulate that firms become more cautious when business is weak, then we would expect more Knightian responses when the outlook on the future is worse.

The results of this section make use of another part of the uncertainty module, dedicated to quantitative forecasting performance, also described in detail in Bachmann et al. (2018). In particular, the module elicits sales growth realized over the last quarter and the firm's forecast for sales growth for the current quarter. Moreover, it asks firms to provide best case and worst case scenarios for sales growth for the current quarter. The idea behind this design was to exploit the widespread use of scenario analysis in German firms to measure subjective uncertainty. Bachmann et al. (2018) propose to use the difference, or *span*, between best and worst case scenarios as a measure of subjective uncertainty. Meta-survey answers show that firms indeed report plausible, as opposed to extreme, scenarios when filling out the questionnaire.

Figure 2.3: Response shares



Notes: Data: pooled responses for all firm quarters 2013-17. Solid lines are fitted values from kernel-weighted local polynomial regressions, shaded areas are 95% confidence intervals. All regressions use polynomials of degree zero and Epanechnikov kernels with bandwidths given by the rule-of-thumb bandwidth estimator. Independent variable on horizontal axis is always one quarter-ahead sales growth forecast at beginning of quarter. Dependent variables are: in left panel, share of certain responses in all responses (blue) and share of Knightian responses in all responses (red), bandwidths are $h = .92$ and $h = 2.67$, respectively; in right panel: Knightian responses as a share of uncertain responses, bandwidth is $h = 1.52$.

We show first that firms tend to give more Knightian responses when their forecast is closer to zero. This is exactly when we would expect the event "sales increase" to be more uncertain: firms with very high or low forecasts are presumably more confident about whether the event will occur or not. The left panel of Figure 2.3 measures the sales forecast along the horizontal axis and displays shares of certain and Knightian responses as a share of all responses. Here we report fitted values from a kernel-weighted local polynomial regression together with shaded 95% confidence intervals.[5] The key result is the inverse U-shape in the share of Knightian responses, with a peak close to zero. In contrast, firms that predict very high or low growth, tend to be sure about the path of future sales, especially when that path is going down.

Figure 2.3 further shows that uncertain firms tend to give more Knightian responses when their predicted sales growth is lower. Indeed, the right panel shows the Knightian share out of uncertain firms: it is a downward sloping function of the forecast. While the Knightian share at a forecast of zero is about the average share of 28%, it increases to close to 40% for forecasts below negative 5%; it is fairly flat for positive forecasts except that it drops below 20% for very high forecasts. The shape suggests some correlation between news that leads firms to pessimistic forecasts and those that change the nature of uncertainty perceived by firms.

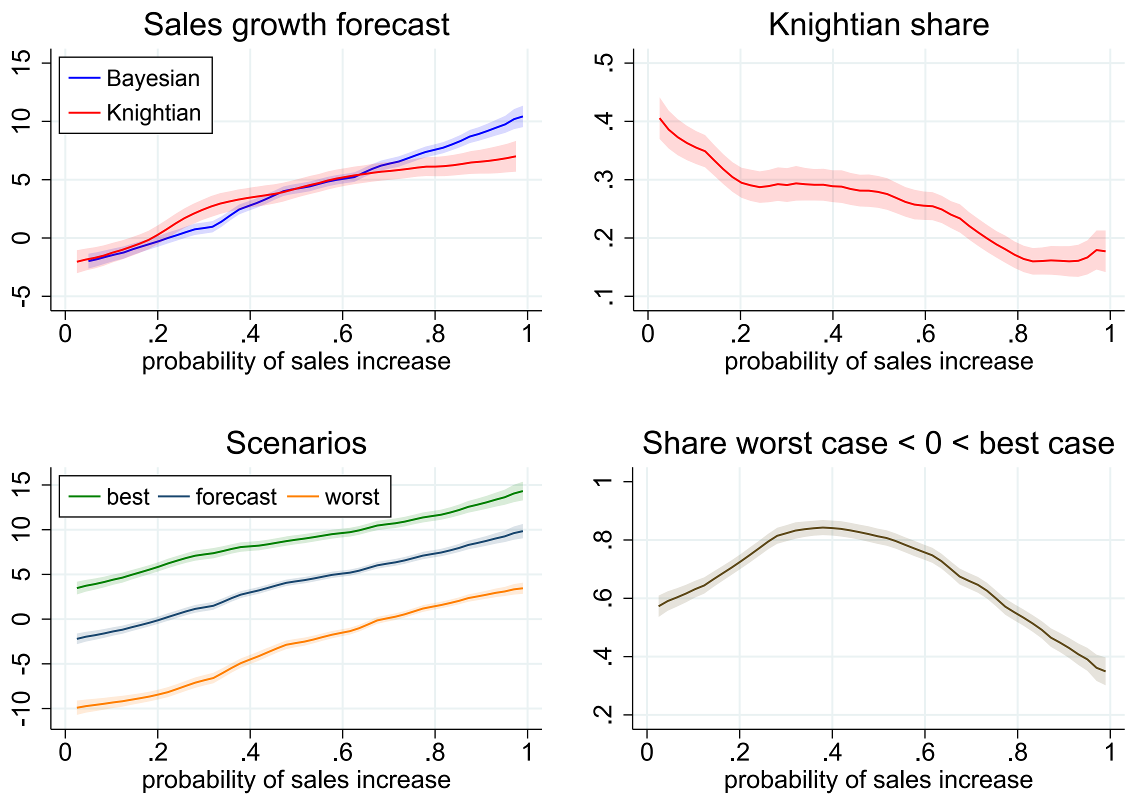
Figure 2.4 relates the Knightian share to best and worst case scenarios contemplated by the firms. This relationship reinforces the two themes seen already: Knightian responses increase with uncertainty and in bad times. The horizontal axis in the figure measures the location of a firm's probability interval, defined as the midpoint for Knightian responses and the single probability in the Bayesian case. For all regressions in this figure, we use an Epanechnikov kernel with a bandwidth of 0.078. This choice is motivated by the empirical distribution of midpoint probabilities: although they are continuous choice variables, firms tend to cluster their answers on multiples of 5% and 10%. The choice of bandwidth is thus effectively a choice of how many such "gridpoints" we include in the neighbourhood of each point. In particular, the smallest bandwidth that includes three (four) neighbour gridpoints to each side is 0.067 (0.089). Our choice of 0.078 sits in the middle between these options.[6]

The top left panel clarifies that the midpoint probability as a measure of location is highly correlated with the sales forecast, for both Bayesian and Knightian responses. The top right panel plots the Knightian share: we again have a downward sloping relationship with a flat middle section. We note also the kink at zero – the share of Knightian responses rises sharply once forecasts turn negative. The panels together

[5] We use a polynomial of degree zero and an Epanechnikov kernel with bandwidth h that is chosen for each regression separately by the rule-of-thumb bandwidth estimator.

[6] To see how our choice weights neighboring gridpoints, consider the following example. Suppose a target point x_0 has exactly three neighbours to the left at gridpoints $x_0 - 0.15$, $x_0 - 0.1$, and $x_0 - 0.05$ and three neighbours to the right at gridpoints $x_0 + 0.05$, $x_0 + 0.10$, and $x_0 + 0.15$. The Epanechnikov kernel is defined as $K_h(z_i) = \frac{3}{4\sqrt{5}h}(1 - 0.2(z_i/h)^2)$ if $|z_i| \leq \sqrt{5}h$ and zero otherwise, where z_i denotes the distance of a grid point to x_0. By choosing $h = 0.078$, the smoothing window thus extends from $x_0 - 0.175$ to $x_0 + 0.175$. The smoothed value at x_0 is the weighted average $\sum_i w_i x_i$, where $x_i = x_0 - 0.15, x_0 - 0.10, \ldots, x_0 + 0.15$. The weights $w_i = K_h(z_i) / \sum_i K_h(z_i)$ generated by the Epanechnikov kernel are then 0.056, 0.143, 0.195, 0.212, 0.195, 0.143 and 0.056.

Figure 2.4: Predicted probabilities of a sales increase, forecasts, and scenarios



Notes: Data: pooled responses for all firm quarters 2013-17. Solid lines in all panels show fitted values of kernel-weighted local polynomial regressions; shaded areas are 95% confidence intervals. All regressions use polynomial of degree zero & Epanechnikov kernel with bandwidth $h = 0.078$. Independent variable along horizontal axis in all panels is midpoint of probability interval for sales increase over current quarter from survey wave at beginning of quarter, with Bayesian responses coded as degenerate intervals (that is, single probabilities). Dependent variables, all from same survey wave as probability intervals are: in top left panel, sales growth forecast for current quarter; in top right panel, share of Knightian responses in uncertain responses in current quarter; in bottom left panel: best and worst case scenarios for current quarter; in bottom right: share of responses s.t. the worst case scenario < 0 < best case scenario.

clarify in what sense the average Knightian response is more pessimistic than the average Bayesian response. Indeed, we can decompose the average (midpoint) forecast of Bayesians and Knightians into two components: the distribution of midpoint beliefs reported in Table 2.2 and implicit in the right panel, and the forecast conditional on that midpoint belief shown in the left panel. The results show that average pessimism is driven exclusively by the former.

Figure 2.4 also points out that, *in good times*, firms give more Knightian responses when their best and worst case scenarios contain zero. Whether the scenarios bracket zero is another natural sense in which firms perceive the event "sales increase" as uncertain. We show the fact in two ways. First, the left hand panel displays the average best and worst case scenarios together with the forecast. The worst case scenario crosses zero at a probability of 67%, right when the Knightian share in the top right panel shows a sharp downward turn. Second, the right hand panel of the figure displays the share of responses such that zero is in between the best and worst cases. Again the dropoff on the right aligns clearly with the dropoff in the Knightian share.

The results of this section are interesting for an ongoing debate on how to interpret survey forecast data. One view holds that respondents who perceive greater uncertainty tend to “shade” their forecasts towards outcomes that are worse for them. For example, risk averse agents might report forecasts derived from a "risk neutral" probability that places more mass on bad events. Similarly, one might suspect that agents who give Knightian responses align their forecasts with their minimum probabilities, and therefore produce more pessimistic forecasts than Bayesians. Our findings instead show that firms with the same *midpoint* probability - whether Bayesian or Knightian – make similar forecasts.

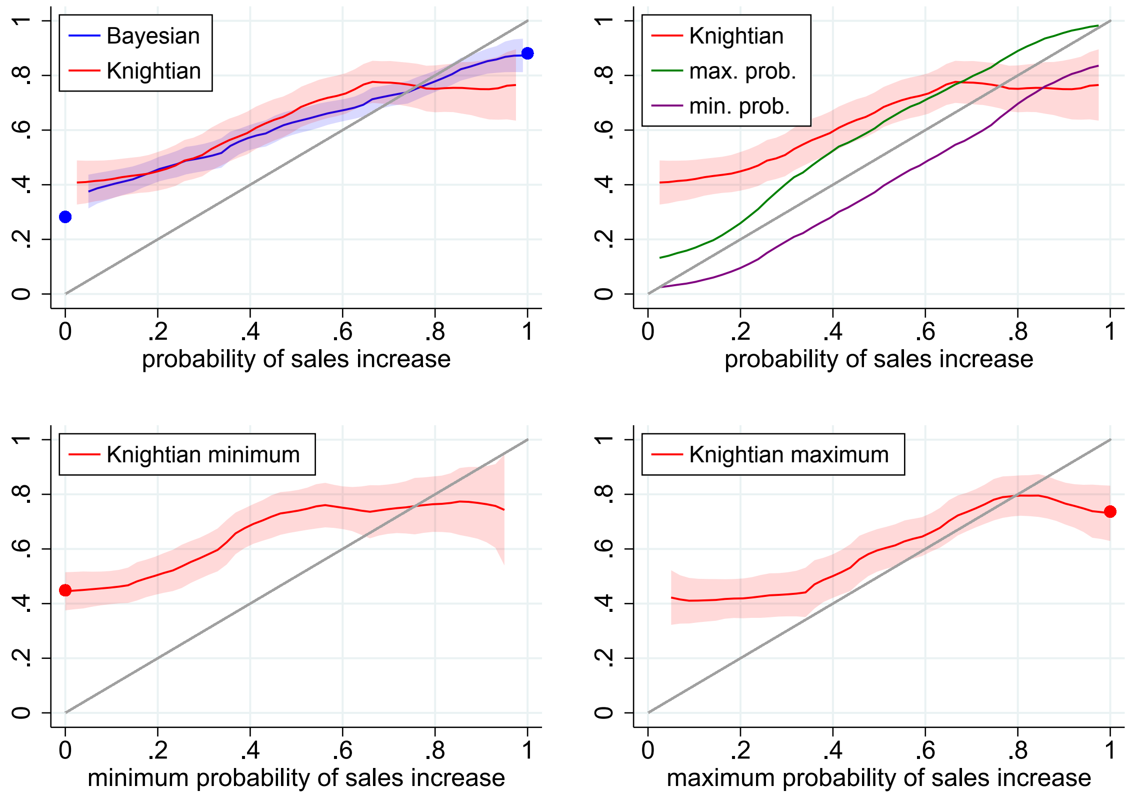
2.3.3 Calibration

Our results on firms’ self assessment in Section 2.3.1 do not suggest that Knightian responses are due to lack of sophistication. However, firms’ subjective view of their planning might not be backed up by their forecasting performance. In this section, we assess that performance by asking how well calibrated firms are as predictors of their own sales growth, and whether there are important differences between Bayesian and Knightian responses. We emphasize that the analysis again takes places at the level of responses, so the question is whether firms forecast systematically worse in quarters when they express their uncertainty in a Knightian fashion.

Our tool to measure calibration is a standard calibration plot, shown in Figure 2.5. For the Bayesian case, the horizontal axis measures the predicted probability whereas the vertical axis measures the frequency with which the predicted event occurred in the data. Well-calibrated forecasters should locate along the 45 degree line: while forecasts are not perfect (away from the endpoints), the realizations of the random variable being forecasted exactly reflect the predicted distribution. A forecaster above (below) the diagonal systematically underpredicts (overpredicts) the event. This graphical analysis has a long history in measuring forecaster performance.

We produce the graph with our pooled sample of forecasts: formally, we run a kernel regression of a dummy indicating a sales increase on the predicted probability. We thus assess the average degree of calibration for groups of firm decision makers that provide the same probability. To extend the analysis to Knightian responses, we use again the midpoint probability as a measure of location of the probability interval. In the top left panel of Figure 2.5, the blue line represents Bayesian responses and the red line represents Knightian responses. The endpoints, that is, the certain responses of zero or one, are plotted separately, that is, they do not inform the kernel regression.

Figure 2.5: Calibration plot



Notes: Data: pooled responses for all firm quarters 2013-17. Solid lines in all panels show fitted values of kernel-weighted local polynomial regressions; shaded areas are 95% confidence intervals. All regressions use polynomial of degree zero and Epanechnikov kernel with bandwidth $h = 0.078$. Top left panel shows separate regressions for Bayesian and Knightian responses in blue and red, respectively. Independent variable on horizontal axis is midpoint of probability interval for sales increase, with Bayesian responses coded as degenerate intervals (= point probabilities). Dependent variable is dummy for occurrence of a sales increase in quarter for which probability forecast is made. Top right panel shows Knightian responses only: red line is same as in top left panel. Green and purple lines are fitted values from regressions of maximum and minimum probabilities on midpoint probability, respectively. Bottom panels show Knightian responses only: dependent variable is dummy for occurrence of a sales increase in quarter for which probability forecast is made; independent variables along horizontal axis are minimum and maximum probabilities in left and right panels, respectively.

The main result is that both Bayesian and Knightian responses are miscalibrated in a very similar fashion: both strongly underestimate the likelihood of a sales increase when their outlook on the future is bad (that is, when their probability of a sales increase is low), and both overestimate it when the outlook is good (that is, when their probability of a sales increase is high). Indeed, both kernel regression lines are much flatter than the 45-degree-line, with an intercept above .4 and an average slope of about

.35. According to the fitted values, Knightians' midpoints imply a larger forecast error when they are between .5 and .7, as well as when they are larger than .8. However, gaps are typically below 10pp and not significantly different from zero. For Bayesians, the pattern is familiar from earlier studies. It is consisted with a simple model of Bayesian updating when agents receive unbiased signals but overestimate their precision: agents then "overreact" to both positive and negative signals.

The other panels of Figure 2.5 focus on Knightian responses only and show that our conclusion is robust to alternative ways of measuring miscalibration. Since Knightian responses consist of an entire probability interval, focusing on the midpoint is only one way to assess calibration, albeit a convenient one that allows familiar graphical analysis. More generally, we would like to know whether the empirical frequency of the forecasted event is contained in the Knightian forecaster's interval. If we had long panel data on each forecaster, this question could be answered directly. Here we draw on the pooled sample to obtain two partial answers.

The top right panel of Figure 2.5 assesses whether the empirical frequency of a sales increases for Knightians with a given midpoint probability is located within the average probability interval predicted by those firms. Formally, we compare fitted values from three kernel regressions on the midpoint probability: a red line for the dummy for a sales increases as in the top left panel, and purple and green lines for the lower and upper of the interval, respectively. If all Knightians were well calibrated, we would see the frequency lie in between the upper and lower bound. We find that Knightian responses are well calibrated in this sense for a range of relatively high midpoint probabilities between 60 and 80 percent. However, for low midpoints the empirical frequency is well above the maximum probability. We can conclude that the typical firm with a bad outlook is also miscalibrated according to this less stringent criterion. There is also some evidence of miscalibration at the very top: here the empirical frequency is below the average minimum probability, that is, the average interval lies entirely above the frequency.

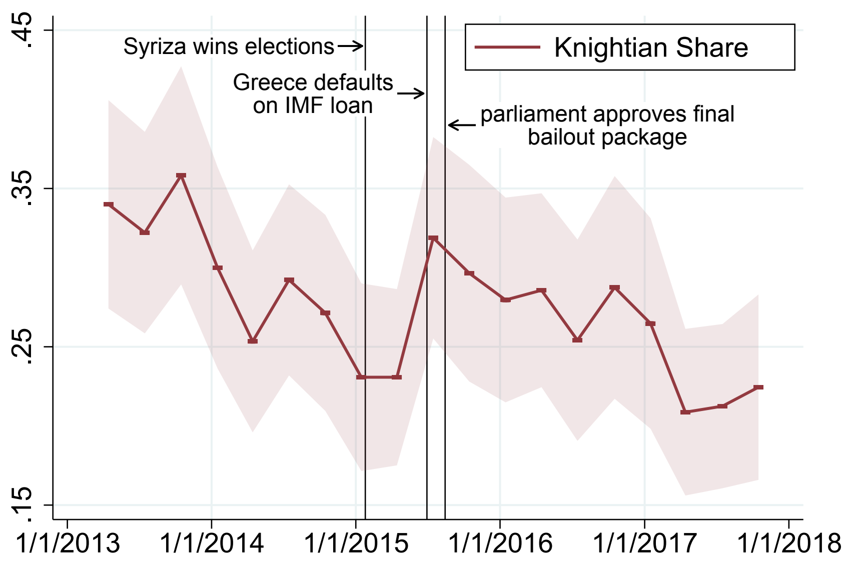
The bottom panels of Figure 2.5 assess miscalibration by directly comparing the empirical frequency to minimum and maximum probabilities: we plot fitted values of kernel regressions of a sales increase dummy on the minimum and maximum probabilities. The panels thus differ from those in the top row in that the horizontal axis no longer measures location but instead interval bounds. This approach avoids averaging the interval bounds across responses with the same midpoint. At the same time, each plot only checks miscalibration in one direction: if Knightian responses are well-calibrated then the empirical frequency lies above the diagonal in the left panel *and* below the diagonal in the right panel.

The bottom left panel zeros in on miscalibration due to overestimation: a frequency of sales increases below the 45-degree line means that the average interval of a firm with this minimum probability is strictly above the empirical frequency. We see this only for the highest minimum probabilities. In contrast, the right panel is set up to uncover miscalibration due to underestimation: a frequency of sales increase above the 45-degree line means that the average interval of a firm with this maximum probability is strictly below the frequency. There is again strong evidence of underestimation.

2.4 Dynamics of Knightian Responses

In this section, we study the evolution of Knightian responses over time. Figure 2.1 displays the evolution of the Knightian share over our sample period, together with shaded 95% confidence bounds. There are two key takeaways. First, the share of *ever-Knightian* firms that give a Knightian response in any given quarter lies between 20 and 35 percent, far below the 76% of firms that give a Knightian response at least once. It follows that firms must frequently switch between Bayesian and Knightian responses. Section 2.4.1 explores whether firm characteristics can predict the frequency of such switches.

Figure 2.1: Time-variation of Knightian share



Notes: Time series of the fraction of Knightian responses by survey wave from 2013Q2 through 2017Q4. Rectangular markers indicate survey periods during the first month of each quarter. The shaded area represents 95% confidence intervals. The vertical lines indicate three important dates of the Greek sovereign debt crisis in 2015.

The second takeaway from Figure 2.1 is that time series movement in the Knightian share appears to reflect macroeconomic risk. In the beginning of the sample, the Knightian share declines as the European debt crisis becomes more distant. It then spikes sharply in early 2015 when the Greek crisis worsens, only to again resume its downward trend later that year. Greek elections on January 25, 2015 saw the victory of the Syriza party that had promised substantial debt write-offs during the campaign. In subsequent months, tensions with Greek's creditors, the so-called Troika, amplified and peaked when Greece, after announcing bank holidays and imposing capital controls, did not repay an IMF loan on June 30. In July, the German minister of finance advocated a temporary exit of Greece from the euro area. On August 14, after more than a month of negotiations, the Greek parliament approved the final of three new bailout programs that gradually allayed financial market fears. Section 2.4.2 compares movement in the Knightian share to other measures of macroeconomic risk and also computes the contribution of firms with a plausibly different exposure to aggregate conditions, e.g., exporting versus non-exporting firms.

2.4.1 The Persistence of Knightian Spells in the Cross Section

Table 2.1 provides an overview of Knightian shares and the dynamics of responses for different classes of firms. The first column lists the Knightian share, that is, Knightian responses as a share of all uncertain responses. The second and third columns measure the frequency of switching to and away from a Knightian response, respectively: we compute empirical conditional probabilities of responses for firms that we observe to be uncertain in two consecutive quarters. These numbers can also be interpreted in terms of duration: assuming a Markovian evolution of the response type, the inverse of the numbers in the second and third column represent the average duration of Bayesian and Knightian spells, respectively. Finally, the fourth column shows the share of ever-Knightian firms that provide a Knightian response at least once in the sample.

We measure firm size by the number of employees, and report results for *large* firms with more than 250 workers as well as *small* firms with 50 or less workers. The ifo survey also indicates whether the firm exports. When asked for their expectations about export business in the next three months, respondents can either choose from the three categories "increase", "unchanged", or "decrease", or tick the option "we do not export". We define firms to be exporters if they always respond with one of the three directional answer options in our sample. The average share of exporting firms is 82%. Finally, we distinguish firms by their average growth rate over the en-

Table 2.1: Knightian (K) and Bayesian (B) responses for different groups of firms

	K share responses	Prob(K | B) responses	Prob(B | K) responses	ever-K share firms
average	0.27 (0.01)	0.19 (0.01)	0.55 (0.03)	0.76 (0.02)
small	0.32 (0.02)	0.20 (0.02)	0.43 (0.05)	0.85 (0.03)
large	0.26 (0.02)	0.21 (0.03)	0.63 (0.06)	0.74 (0.04)
non-exporter	0.35 (0.03)	0.21 (0.03)	0.43 (0.06)	0.85 (0.04)
exporter	0.26 (0.01)	0.19 (0.01)	0.58 (0.03)	0.73 (0.02)
low growth	0.31 (0.02)	0.20 (0.03)	0.50 (0.06)	0.79 (0.04)
high growth	0.24 (0.02)	0.16 (0.02)	0.55 (0.06)	0.70 (0.05)

Notes: Column 1 shows share of Knightian responses in pooled sample of 4646 firm quarters. Columns 2 & 3 show empirical transition probabilities in subsample of 1790 firm-quarters such that each firm is represented in quarters t and $t+1$. Column 2 (3) shows firm date pairs such that Bayesian (Knightian) response at t is followed by a Knightian (Bayesian) response at $t+1$, as a share of firm date pairs with Bayesian (Knightian) responses at t. Column 4 shows share of ever-Knightian firms that respond at least once as Knightian, based on 422 firms with at least five uncertain responses. Rows refer to full sample as well as subsample averages. Small firms have 50 or less employees, large firms have more than 250 employees, exporter firms report they export in every quarter they appear in the sample, while non-exporter do not, low and high trend growth firms are defined as bottom and top quartile of the firm-average sales growth distribution.

tire five year sample. The idea here is that beliefs about sales growth may not only depend on size but also on the firm's trajectory. We form four quartiles of firms by average growth rate and report here the top and bottom quartiles, labeled high and low growth, respectively. Average growth rates over the sample within these groups are -4.8% and 9.6%, respectively.

The first result from the table is that there are statistically significant, if economically moderate, differences in the Knightian shares across firms. In particular, Knightian responses are more prevalent among small firms, firms that do not export as well as firms with low growth trends. While there is correlation between these characteristics – in particular large firms tend to be exporters – separate regressions (not reported) show that each characteristic has an independent impact on the frequency of Knightian responses.

The second result is that firms in groups with large fractions of Knightian responses experience longer Knightian spells, but do not necessarily start more of those spells. This is apparent from the second column: for size and export share, the probabilities of switching to Knightian are all very close to 20%. At the same time, probabilities in the third column reveal large differences in the duration of Knightian spells: while it is only 1.52 quarters for large as well as for exporting firms, it rises to 1.72 quarters for non-exporting firms and to 2.32 quarters for small firms. For both of those groups the larger share of ever-Knightian firms in the fourth column is thus explained largely by longer Knightian spells.

The groups of high and low trend firms behave differently. Here we do see a significantly lower probability of switching to a Knightian response for firms that grow faster on average. Moreover, while Knightian spells are longer for low growth firms, the cross group difference in probabilities in the third column is much smaller than for the other pairs of groups. We can conclude that growth trend also helps predict the frequency of Knightian responses. In contrast to the other characteristics, however, this is not only because the duration of Knightian spells is predictable. In addition, it is actually possible to predict the frequency of switches to Knightian responses.

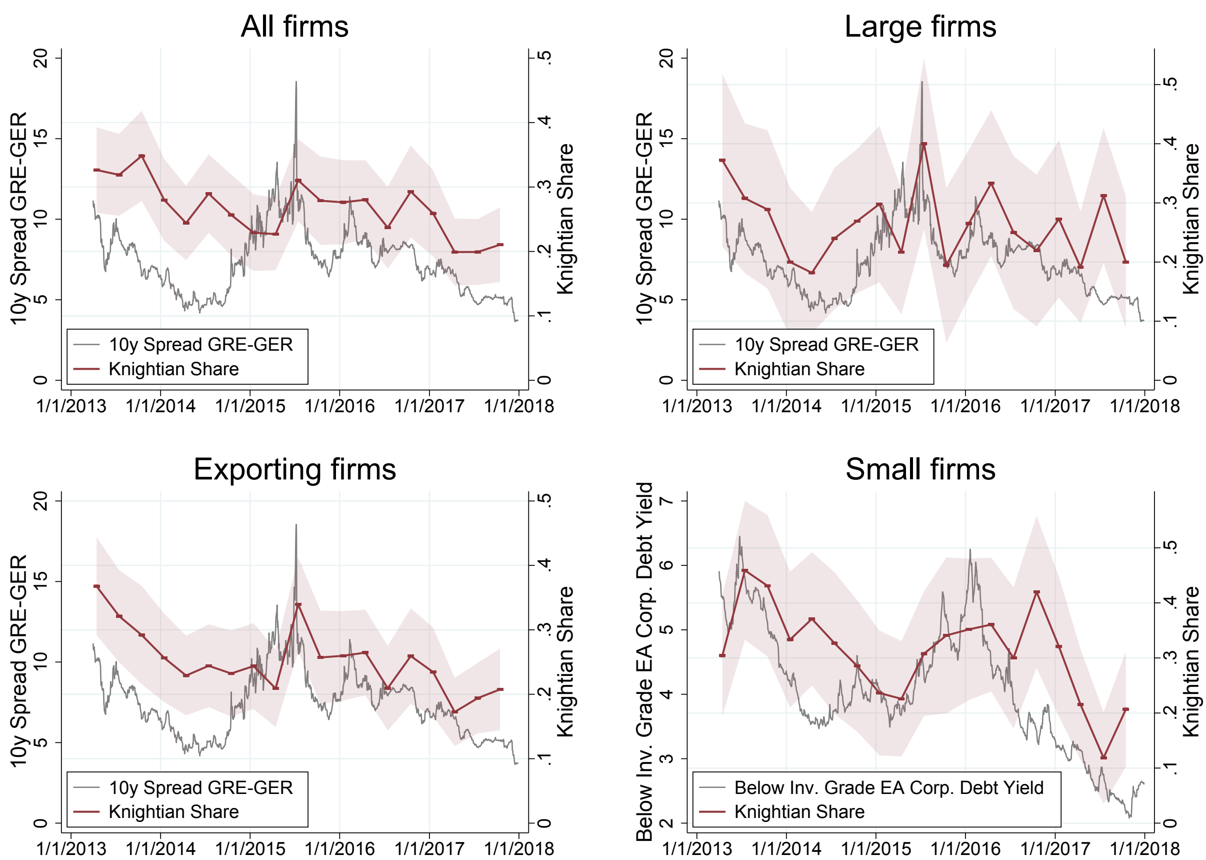
2.4.2 Knightian Responses and Macroeconomic Risk

We now return to the time series evolution of the Knightian share in Figure 2.1. To further understand this evolution, Figure 2.2 plots Knightian shares for different groups of firms, and also overlays it with two types of credit spreads, key measures of macroeconomic risk during recent boom bust episodes. Theories of Knightian uncertainty tend to emphasize that it should be reflected jointly in firm planning and observed risk premia in financial markets. In each panel, Knightian shares are presented with 95% confidence intervals and measured along the left vertical axis. Credit spreads are measured along the right vertical axis.

The top left panel compares the overall Knightian share with the spread between Greek and German bonds. The co-movement is striking: like the Knightian share, the sovereign risk spread goes through the three phases of initial decline, upward spike, and recovery. As the Greek crisis unfolds, the spread leads the Knightian share by two quarters: we observe an elevated Knightian share only at the beginning of the third quarter of 2015, that is, in early July. The top right panel shows that the Knightian share for large firms – which are presumably more connected to international markets – ticks up already 6 months earlier, at the same time when spreads widen.

The bottom left and right panels look at exporting firms – likely more exposed to an international event – and small firms, respectively. Much like large firms, exporters give fewer Knightian responses most of the time, but experience a notable spike right at the peak of the Greek crisis. A key difference to large firms is that their reaction comes with a lag. Small firms differ from both the other groups in that the 2015 increase in the Knightian share is rather mild, but builds up to a protracted increase. This fact is connected to the longer duration of Knightian spells experienced by the typical small firm. As a result, the path of average Knightian uncertainty experienced by small firms resembles less the Greek spread, a measure of financial stability in Europe, but instead a high yield spread, often taken as a measure of financial frictions.

Figure 2.2: Time-variation of Knightian share with financial measures of macroeconomic risk



Notes: Time series of the fraction of Knightian responses by survey wave from 2013Q2 through 2017Q4. We show this series for all firms, as well as for the subsamples of large firms with more than 250 employees, exporting firms defined as firms that always reported to export in our sample, and small firms with 50 employees or less. The rectangular markers illustrate the survey periods in the first month of a quarter. The shaded area represents 95% confidence intervals. We plot the Knightian share series against financial series: the 10-year Greek government bond spread against the 10-year German government bond (top row of plots and bottom left) and the yield of below investment grade euro area corporate debt. The former is retrieved from Macrobond, the latter is taken from the FRED data base (FRED identifier: BAMLHE00EHYIEY).

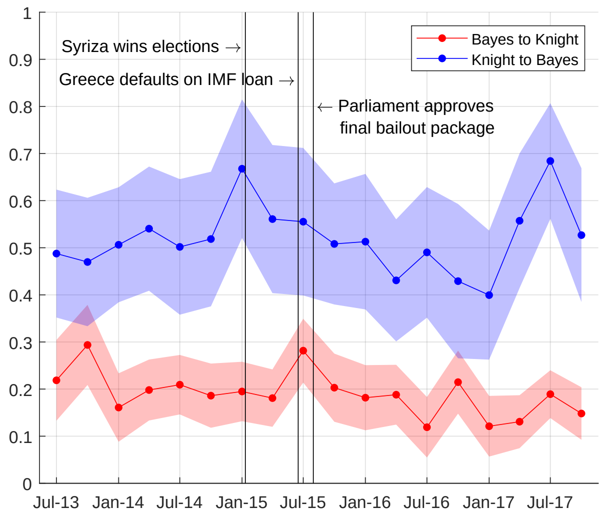
2.4.3 Transition Dynamics Between Bayesian and Knightian Responses

We have shown above that the share of Knightian responses varies over time and is meaningfully related to macroeconomic events. We now study how switching between Bayesian and Knightian states contribute to changes in the Knightian share. To this end, we estimate a two-state Markov chain that takes on the values "Bayes" or "Knight". We allow transition probabilities to depend on calendar time. We handle missing values in our unbalanced panel of firms by taking as observables all realized transitions between states by firms, possibly more than one quarter apart. We estimate the sequence of transition matrices by maximum likelihood; details are contained in Appendix 2.B for details.

The estimated switching probabilities are displayed in Figure 2.3. They are characterized by substantial time-variation: The probability of switching from a Knightian to a Bayesian response – that is, exiting a Knightian spell – varies between 40 and 70 percent, whereas the probability of entering a Knightian spell varies between 10 and 30 percent. Time variation in both types of transition thus contributes to fluctuations in the Knightian share in Figure 2.1. At the same time, some movements in the Knightian share are not associated with changes in transition probabilities.

Consider in more detail the dynamics of beliefs at the beginning of our sample, that is, the back end of the European debt crisis. The summer of 2013 marked a renewed increase in many risky borrowing rates, including the low quality yield in the bottom right panel of Figure 2.2. The transition matrix from July to October then saw a one time spike in the probability of switching from a Bayesian to a Knightian response. Over the next year and a half, transition probabilities remained essentially constant, which led to a steady exit from Knightian spells. After the ECB's introduction of its QE programs – first announced in September 2014 and extended in January 2015 – there is a large spike in switches from Knightian to Bayesian responses. Finally, the widening of spreads in summer 2015 again coincides with a spike in the probability of entering a Knightian spell.

Figure 2.3: Time varying transition probabilities



Notes: Estimated time-varying transition probabilities from Bayesian to Knightian responses and from Knightian to Bayesian responses 2013Q3 through 2017Q4. Probabilities for quarter t represent transition probabilities from quarter $t-1$ to quarter t. The shaded area represents 95% confidence intervals. Vertical lines indicate three important dates for the Greek sovereign debt crisis in 2015.

2.5 Conclusion

Using survey data from German firms, this paper studies whether executives think about future sales growth in terms of probabilities. In a question about the likelihood of a sales increase we innovate by letting respondents freely decide to submit either a single probability or a "Knightian" probability interval. Our main result is that "Knightian" responses are pervasive: three quarters of the firms in our sample choose a probability interval at least once in five years. Using results from a meta survey and information on their other forecasts, we show that managers use probability intervals to express their lack of clarity about the future; they do not reflect a lack of sophistication. Moreover, responses with probability intervals are equally miscalibrated compared to "Bayesian" responses with single probabilities.

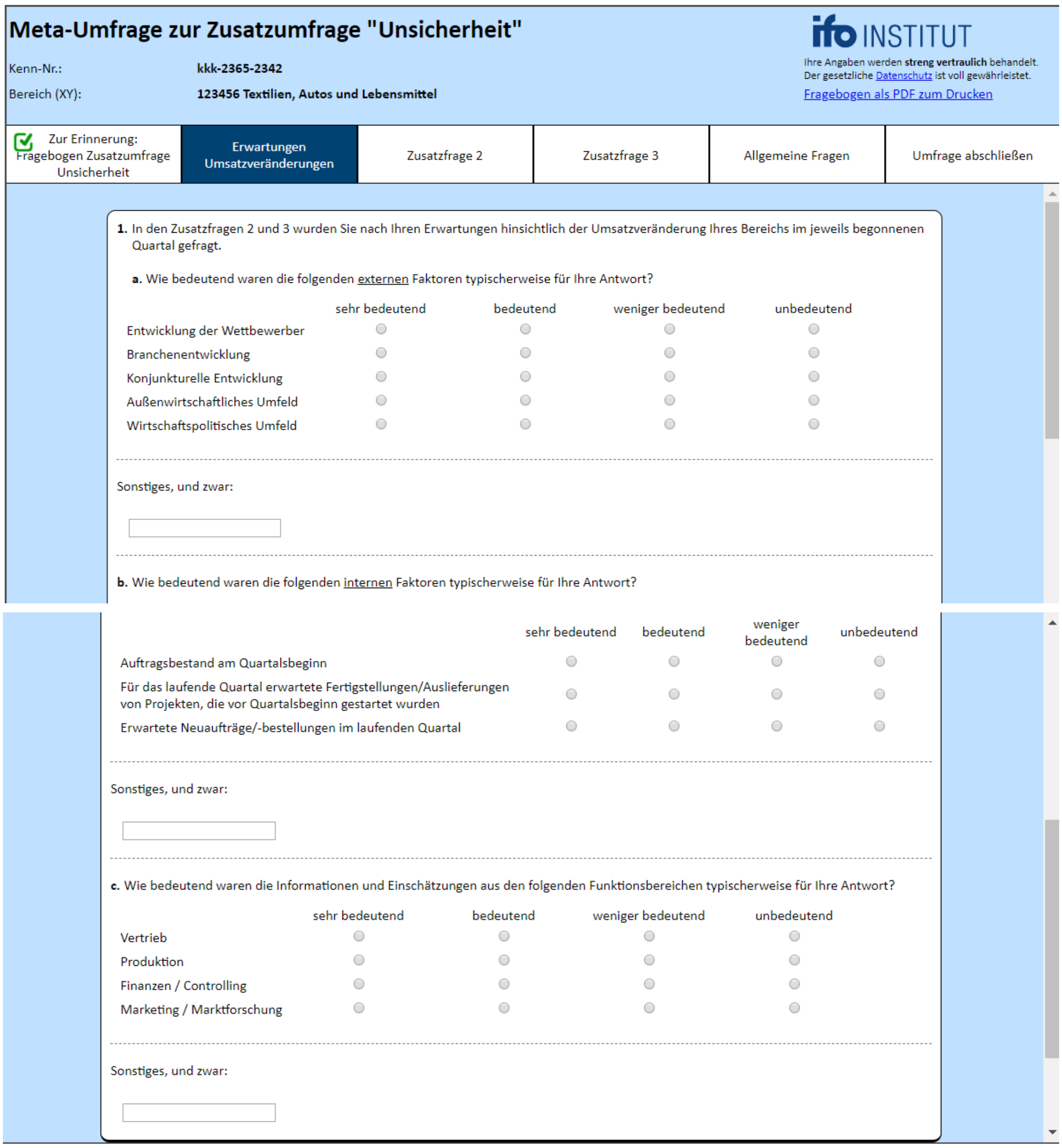
We further document that respondents switch between the "Knightian" and "Bayesian" answer options: they occasionally enter persistent "'Knightian" spells. This behavior seems to reflect both idiosyncratic and aggregate events. During the Greek debt crisis in 2015, the share of "Knightian" responses spikes up in parallel with bond spreads. This is most pronounced for large and exporting firms that would have been most affected – directly or indirectly – by a default or a possible exit of Greece from the euro area.

Quantitative survey question often elicit subjective beliefs of households and decision makers in firms using single probabilities. This equates uncertainty with risk. Our results suggest that a more flexible survey technique can collect richer information reflecting both Bayesian and Knightian perceptions of the future.

Appendix

2.A Questionnaire for the Fall 2018 Meta-Survey

Figure 2.A.1: Original meta survey questionnaire in German, part 1



Meta-Umfrage zur Zusatzumfrage "Unsicherheit"

ifo INSTITUT

Kenn-Nr.: kkk-2365-2342

Bereich (XY): 123456 Textilien, Autos und Lebensmittel

Ihre Angaben werden **streng vertraulich** behandelt.
Der gesetzliche Datenschutz ist voll gewährleistet.
Fragebogen als PDF zum Drucken

Zur Erinnerung: Fragebogen Zusatzumfrage Unsicherheit	Erwartungen Umsatzveränderungen	Zusatzfrage 2	Zusatzfrage 3	Allgemeine Fragen	Umfrage abschließen

1. In den Zusatzfragen 2 und 3 wurden Sie nach Ihren Erwartungen hinsichtlich der Umsatzveränderung Ihres Bereichs im jeweils begonnenen Quartal gefragt.

a. Wie bedeutend waren die folgenden externen Faktoren typischerweise für Ihre Antwort?

	sehr bedeutend	bedeutend	weniger bedeutend	unbedeutend
Entwicklung der Wettbewerber				
Branchenentwicklung				
Konjunkturelle Entwicklung				
Außenwirtschaftliches Umfeld				
Wirtschaftspolitisches Umfeld				

Sonstiges, und zwar:

b. Wie bedeutend waren die folgenden internen Faktoren typischerweise für Ihre Antwort?

	sehr bedeutend	bedeutend	weniger bedeutend	unbedeutend
Auftragsbestand am Quartalsbeginn				
Für das laufende Quartal erwartete Fertigstellungen/Auslieferungen von Projekten, die vor Quartalsbeginn gestartet wurden				
Erwartete Neuaufträge/-bestellungen im laufenden Quartal				

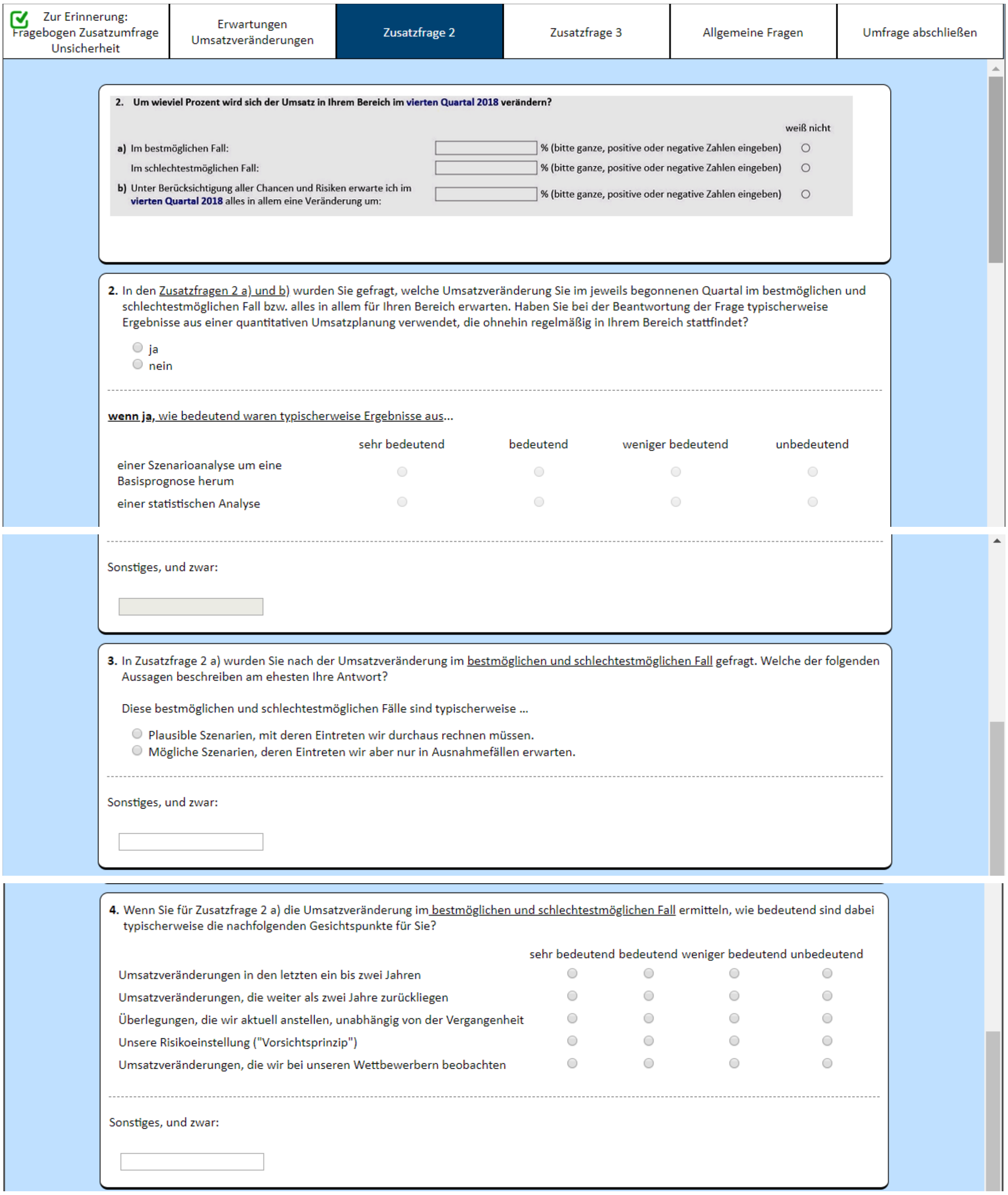
Sonstiges, und zwar:

c. Wie bedeutend waren die Informationen und Einschätzungen aus den folgenden Funktionsbereichen typischerweise für Ihre Antwort?

	sehr bedeutend	bedeutend	weniger bedeutend	unbedeutend
Vertrieb				
Produktion				
Finanzen / Controlling				
Marketing / Marktforschung				

Sonstiges, und zwar:

Figure 2.A.2: Original meta survey questionnaire in German, part 2



Zur Erinnerung: Fragebogen Zusatzumfrage Unsicherheit	Erwartungen Umsatzveränderungen	Zusatzfrage 2	Zusatzfrage 3	Allgemeine Fragen	Umfrage abschließen

2. Um wieviel Prozent wird sich der Umsatz in Ihrem Bereich im vierten Quartal 2018 verändern?

		weiß nicht
a) Im bestmöglichen Fall:	% (bitte ganze, positive oder negative Zahlen eingeben)	○
Im schlechtestmöglichen Fall:	% (bitte ganze, positive oder negative Zahlen eingeben)	○
b) Unter Berücksichtigung aller Chancen und Risiken erwarte ich im **vierten Quartal 2018** alles in allem eine Veränderung um:	% (bitte ganze, positive oder negative Zahlen eingeben)	○

2. In den Zusatzfragen 2 a) und b) wurden Sie gefragt, welche Umsatzveränderung Sie im jeweils begonnenen Quartal im bestmöglichen und schlechtestmöglichen Fall bzw. alles in allem für Ihren Bereich erwarten. Haben Sie bei der Beantwortung der Frage typischerweise Ergebnisse aus einer quantitativen Umsatzplanung verwendet, die ohnehin regelmäßig in Ihrem Bereich stattfindet?

- ja
- nein

wenn ja, wie bedeutend waren typischerweise Ergebnisse aus...

	sehr bedeutend	bedeutend	weniger bedeutend	unbedeutend
einer Szenarioanalyse um eine Basisprognose herum	○	○	○	○
einer statistischen Analyse	○	○	○	○

Sonstiges, und zwar:

3. In Zusatzfrage 2 a) wurden Sie nach der Umsatzveränderung im bestmöglichen und schlechtestmöglichen Fall gefragt. Welche der folgenden Aussagen beschreiben am ehesten Ihre Antwort?

Diese bestmöglichen und schlechtestmöglichen Fälle sind typischerweise ...

- Plausible Szenarien, mit deren Eintreten wir durchaus rechnen müssen.
- Mögliche Szenarien, deren Eintreten wir aber nur in Ausnahmefällen erwarten.

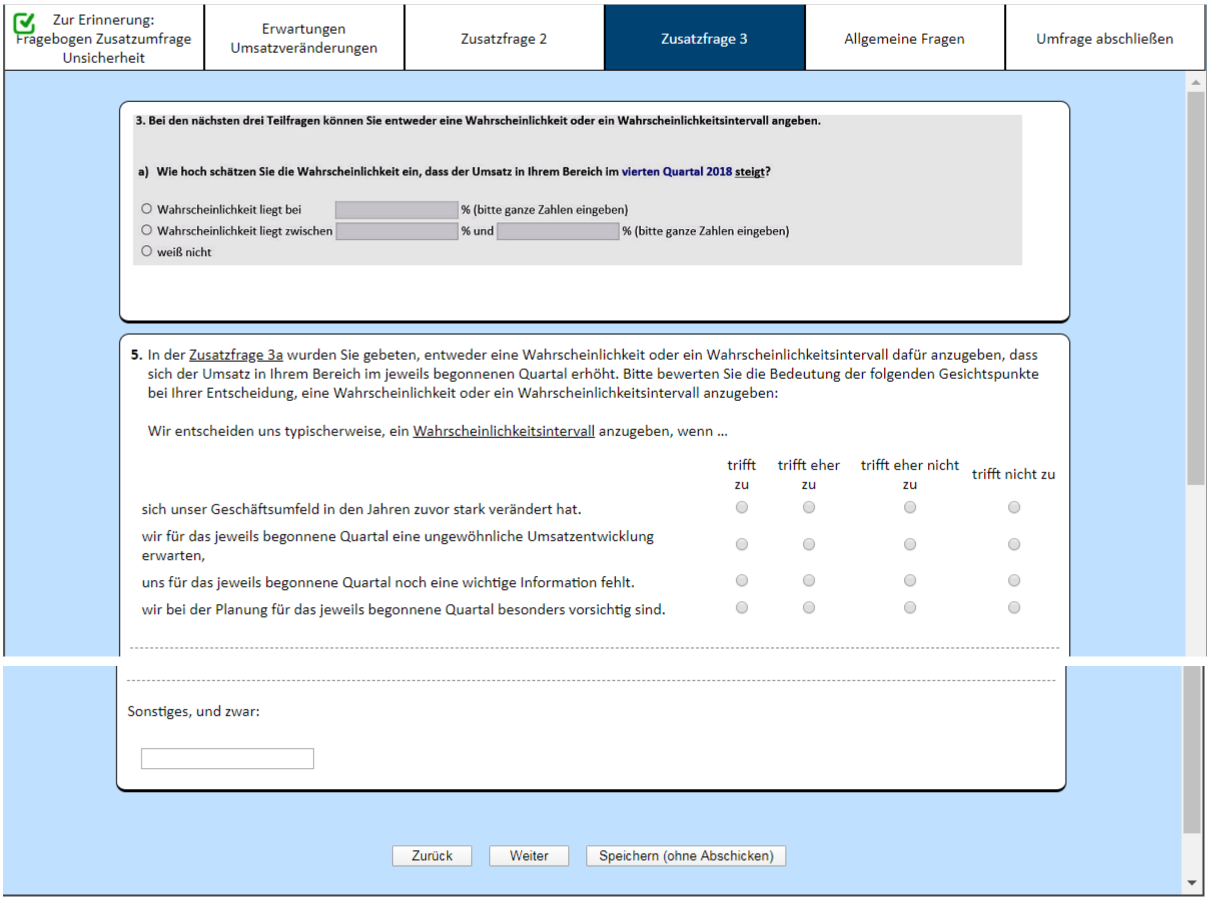
Sonstiges, und zwar:

4. Wenn Sie für Zusatzfrage 2 a) die Umsatzveränderung im bestmöglichen und schlechtestmöglichen Fall ermitteln, wie bedeutend sind dabei typischerweise die nachfolgenden Gesichtspunkte für Sie?

	sehr bedeutend	bedeutend	weniger bedeutend	unbedeutend
Umsatzveränderungen in den letzten ein bis zwei Jahren	○	○	○	○
Umsatzveränderungen, die weiter als zwei Jahre zurückliegen	○	○	○	○
Überlegungen, die wir aktuell anstellen, unabhängig von der Vergangenheit	○	○	○	○
Unsere Risikoeinstellung ("Vorsichtsprinzip")	○	○	○	○
Umsatzveränderungen, die wir bei unseren Wettbewerbern beobachten	○	○	○	○

Sonstiges, und zwar:

Figure 2.A.3: Original meta survey questionnaire in German, part 3



Zur Erinnerung: Fragebogen Zusatzumfrage Unsicherheit | Erwartungen Umsatzveränderungen | Zusatzfrage 2 | Zusatzfrage 3 | Allgemeine Fragen | Umfrage abschließen

3. Bei den nächsten drei Teilfragen können Sie entweder eine Wahrscheinlichkeit oder ein Wahrscheinlichkeitsintervall angeben.

a) Wie hoch schätzen Sie die Wahrscheinlichkeit ein, dass der Umsatz in Ihrem Bereich im vierten Quartal 2018 steigt?

- Wahrscheinlichkeit liegt bei ____ % (bitte ganze Zahlen eingeben)
- Wahrscheinlichkeit liegt zwischen ____ % und ____ % (bitte ganze Zahlen eingeben)
- weiß nicht

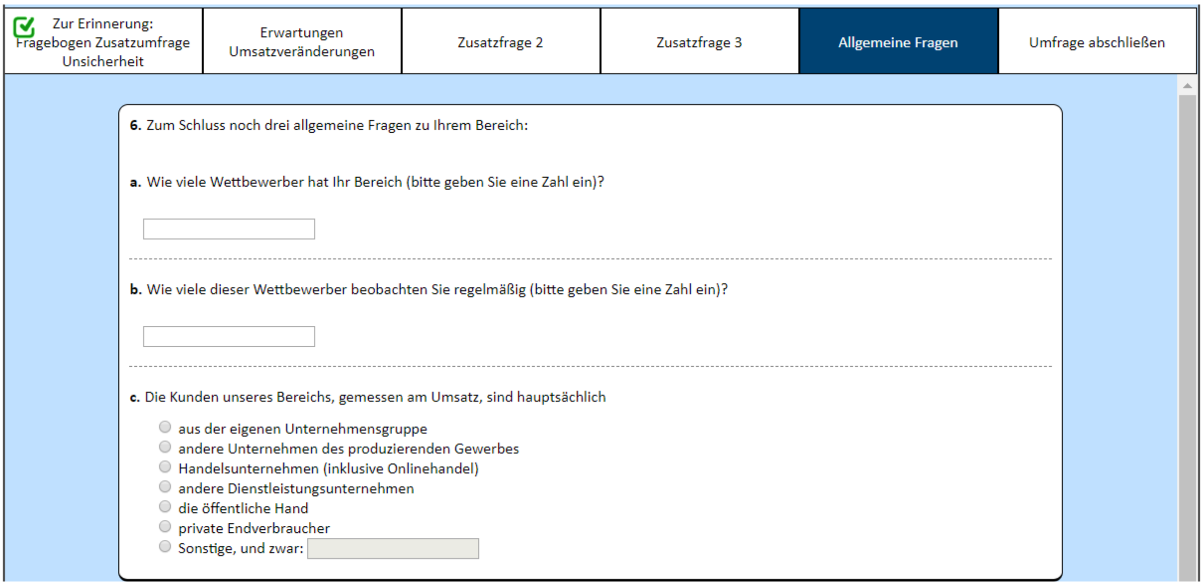
5. In der Zusatzfrage 3a wurden Sie gebeten, entweder eine Wahrscheinlichkeit oder ein Wahrscheinlichkeitsintervall dafür anzugeben, dass sich der Umsatz in Ihrem Bereich im jeweils begonnenen Quartal erhöht. Bitte bewerten Sie die Bedeutung der folgenden Gesichtspunkte bei Ihrer Entscheidung, eine Wahrscheinlichkeit oder ein Wahrscheinlichkeitsintervall anzugeben:

Wir entscheiden uns typischerweise, ein Wahrscheinlichkeitsintervall anzugeben, wenn ...

	trifft zu	trifft eher zu	trifft eher nicht zu	trifft nicht zu
sich unser Geschäftsumfeld in den Jahren zuvor stark verändert hat.	○	○	○	○
wir für das jeweils begonnene Quartal eine ungewöhnliche Umsatzentwicklung erwarten,	○	○	○	○
uns für das jeweils begonnene Quartal noch eine wichtige Information fehlt.	○	○	○	○
wir bei der Planung für das jeweils begonnene Quartal besonders vorsichtig sind.	○	○	○	○

Sonstiges, und zwar:

Zurück | Weiter | Speichern (ohne Abschicken)



Zur Erinnerung: Fragebogen Zusatzumfrage Unsicherheit | Erwartungen Umsatzveränderungen | Zusatzfrage 2 | Zusatzfrage 3 | Allgemeine Fragen | Umfrage abschließen

6. Zum Schluss noch drei allgemeine Fragen zu Ihrem Bereich:

a. Wie viele Wettbewerber hat Ihr Bereich (bitte geben Sie eine Zahl ein)?

b. Wie viele dieser Wettbewerber beobachten Sie regelmäßig (bitte geben Sie eine Zahl ein)?

c. Die Kunden unseres Bereichs, gemessen am Umsatz, sind hauptsächlich

- aus der eigenen Unternehmensgruppe
- andere Unternehmen des produzierenden Gewerbes
- Handelsunternehmen (inklusive Onlinehandel)
- andere Dienstleistungsunternehmen
- die öffentliche Hand
- private Endverbraucher
- Sonstige, und zwar:

2.B Estimation of Transition Matrices

To model the dynamics of the choice between a probability interval ("Knightian" answer) and a point probability ("Bayesian" answer) for the event of a sales increase, we use a discrete Markov chain with two states. To this end, we define the variable y_{it} that can take values (states) 1=Knightian and 2=Bayesian. To save notation, we first describe the construction of the likelihood function for the time-invariant case. The objective is to estimate the parameters of the time-invariant transition matrix

$$P^{(1)} \equiv P = \begin{bmatrix} p_{11} & p_{12} \\ p_{21} & p_{22} \end{bmatrix},$$

where $p_{11} + p_{12} = 1$ and $p_{21} + p_{22} = 1$. For later use, let us also define the h-step transition matrix

$$P^{(h)} \equiv \begin{bmatrix} p_{11}^{(h)} & p_{12}^{(h)} \\ p_{21}^{(h)} & p_{22}^{(h)} \end{bmatrix} = P^h,$$

where $p_{jk}^{(h)}$ are functions of p_{jk}, again with the property $p_{11}^{(h)} + p_{12}^{(h)} = 1$ and $p_{21}^{(h)} + p_{22}^{(h)} = 1$.

We have an unbalanced panel of $i = 1, \ldots, N$ firms. The maximum sample is $t = 1, \ldots, T$ but firms do not respond every period. We assume that each firm i is observed $5 \leq k_i \leq T$ times in periods $t_{i1}, \ldots, t_{ik_i}$, where $1 \leq t_{ij} \leq T$. Hence, the vector y_i of all observations of firm i is

$$y_i = (y_{it_{i1}}, \ldots, y_{it_{ik_i}})'.$$

To write down the likelihood function that includes all relevant information, we factorize the joint pmf into observed conditionals. The Markov property implies that, e.g.,

$$f(y_{it}|y_{it-h}) = p_{y_{it-h}, y_{it}}^{(h)}.$$

Using this result, we write the joint distribution of the observations of firm i as

$$f(y_i) = f(y_{it_{i1}}) \prod_{\kappa=2}^{k_i} f(y_{it_{i,\kappa}}|y_{it_{i,\kappa-1}}) = f(y_{it_{i1}}) \prod_{\kappa=2}^{k_i} p_{y_{it_{i,\kappa}}, y_{it_{i,\kappa-1}}}^{(t_{i,\kappa}-t_{i,\kappa-1})}.$$

Assuming cross-sectional independence of firms, the log-likelihood function is

$$\log L(p_{11}, p_{21}) = \sum_{i=1}^{N} \log f(y_i).$$

Since it includes the parameters of h-step transition matrices, it is highly nonlinear and needs to be maximized numerically.

We now turn to the case of time-varying transition matrices considered in the text.

$$P_t^{(1)} \equiv P_t = \begin{bmatrix} p_{t,11} & p_{t,12} \\ p_{t,21} & p_{t,22} \end{bmatrix}, \quad t = 1, \ldots, T,$$

where $p_{t,11} + p_{t,12} = 1$ and $p_{t,21} + p_{t,22} = 1$. The h-step transition matrix for transition from $t-h$ to t thus is

$$P_t^{(h)} \equiv \begin{bmatrix} p_{t,11}^{(h)} & p_{t,12}^{(h)} \\ p_{t,21}^{(h)} & p_{t,22}^{(h)} \end{bmatrix} = \prod_{j=1}^{h} P_{t-h+j},$$

where $p_{t,11}^{(h)} + p_{12}^{(h)} = 1$ and $p_{t,21}^{(h)} + p_{t,22}^{(h)} = 1$.

The likelihood function is defined analogously to the time invariant case..

Chapter 3

Subjective Uncertainty, Expectations, and Firm Behavior

3.1 Introduction

An active literature is interested in understanding how uncertainty affects individual economic decisions, and as a result, business cycle fluctuations. Similar to expectations, uncertainty is inherently subjective. Thus, a good starting point to analyze how uncertainty affects outcomes are the beliefs of decision makers in firms and households. To guide their actions, individuals form expectations in the presence of uncertainty. Hence, conceptually expectations and subjective uncertainty are closely related. Yet, due to a lack of adequate measures, little is known about their empirical relationship and their relative importance for economic decisions.

This paper presents a new measure of managers' perceived uncertainty and relates it to their expectations and corporate decisions. In particular, I use the results from a novel survey question that asks firms *directly* how uncertain they are about the development of their business. This question is part of the ifo Business Survey, a representative German business survey that covers roughly 9,000 firms each month. Both at the micro level and in the time series, it allows me to develop stylized facts about the relationship between managers' subjective uncertainty vis-à-vis their business expectations over the next six months and their assessment of their current business situation. All three variables are reported on visual analogue scales, which are essentially more differentiated versions of Likert scales. To establish my baseline results, I focus on the manufacturing sector from 2017 to 2019: during this time, it slipped from a boom to a moderate recession. To verify my findings, I extend the analysis to other sectors and to fluctuations of the economy during the subsequent COVID-19 crisis. Exploiting firm heterogeneity and the large aggregate variation in the onset of this crisis, I relate uncertainty and expectations to firms' investment and employment decisions.

My main findings are fourfold. First, asking managers directly about their uncertainty seems to be a sensible method to elicit beliefs. Second, firms' perceived uncertainty about their future business development is strongly negatively related to their business expectations. This stylized fact is manifest both at the micro level and in the time series. Third, I find that this relationship is weaker in bad times. Managers perceive high uncertainty in a period of low economic activity even if expectations improve. Fourth, in contrast to first moment changes, changes in uncertainty neither predict the postponement of investment projects nor a "freeze" of the number of employees in the onset of the COVID-19 crisis. This is not in line with the theoretical mechanism of "wait and see" behavior.

Regarding the measurement of subjective business uncertainty, my first result is that managers have a good understanding of the term "uncertainty"—in the sense of "difficult to predict". This is based on a comparison of the answers to two questions: one that asks respondents directly how *uncertain* they are about their business development and a second one that asks them for an assessment of the *difficulty to predict* this development. I document that the responses to the two questions essentially contain the same information. Conceptually, both questions are holistic and able to capture not only risk, but also Knightian uncertainty.[1] In case of risk, the second question is a measure of variance. In sum, this suggests that a direct question can be a sensible tool to measure firms' subjective uncertainty.

Using firm-level data from the manufacturing sector, my second result is that perceived uncertainty is strongly negatively related to business expectations and respondents' assessment of the current business situation. Based on bivariate relationships, the more pessimistic a respondent or the worse her assessment of the business situation, the more uncertain she is. This holds true both for the pooled sample and within firms. However, the relationships are not linear. The negative relationship is stronger when firms are pessimistic compared to when they are optimistic. These findings recall the inverse relationship of expected returns and volatility observed in equity markets (see, for instance, Bekaert and Wu 2000). Managers' expectations and subjective uncertainty seem to behave similarly to these financial market outcomes.

Next, I study how perceived uncertainty is related to *combinations* of the assessment of the business situation and expectations. Two cases are of particular interest: a good business situation combined with unfavorable expectations, and a bad business situation combined with favorable expectations. From an aggregate view, many such instances might correspond to business cycle turning points. Based on the micro data, I find that uncertainty is high in both cases. Overall, it emerges as a stylized fact that managers are highly uncertain if either the situation is assessed as poor or expectations are unfavorable, or both. Since in a bad situation uncertainty is always high, the relationship between uncertainty and expectations is weaker in bad times. These findings suggest that managers' uncertainty increases when expectations deteriorate, it stays high in a bad business situation, and it only decreases when the business situation normalizes. Further below, I provide a tentative intuition for this pattern based on the negatively skewed distribution of firms' growth rates.

The stylized facts from the micro level carry over to the time series for the manufacturing sector. The central and novel result is that perceived uncertainty and expectations are almost perfectly inversely correlated in the aggregate. The same is true for the re-

[1] The categorization of uncertainty in risk and Knightian uncertainty (or "ambiguity") dates back to Knight (1921). In today's understanding, risk refers to a situation in which individuals can assign probabilities to a set of future events, while this is not possible in the case of Knightian uncertainty.

lationship between uncertainty and the business situation. This confirms the stylized fact from proxy measures which indicate that uncertainty is counter-cyclical. Moreover, in line with the micro evidence, the relationship between uncertainty and expectations appears to be state-dependent: uncertainty correlates less with expectations if the average business situation in unfavorable.

I demonstrate the validity of these time series results along several dimensions. First, the inverse relation between uncertainty and expectations holds for all major sectors—namely manufacturing, construction, retail and wholesale trade, and services—and the German economy as a whole. Moreover, it becomes especially apparent during the COVID-19 crisis in the first half of 2020. By mid-2020, expectations improve, but uncertainty persists, as the economy stays weak. These stylized facts hold true for three different measures of subjective uncertainty. Data from the Survey of Business Uncertainty administered by the Federal Reserve Bank of Atlanta displays a similar pattern for the US.

The simultaneity of aggregate movements in subjective uncertainty and expectations challenges traditional recursive identification schemes in vector-autoregressive frameworks that attempt to causally link uncertainty to outcomes. Due to possible endogeneity of uncertainty and growth, Ludvigson et al. (2020) also view other identification strategies used in time-series econometrics as problematic. This applies in particular to recessions, when uncertainty fluctuates the most. Using micro data offers an alternative way to learn about the effect of uncertainty on outcomes. It has two advantages. First, besides time-series variation, also differences in the cross section can be exploited. Second, it provides the opportunity to directly test theoretical channels that connect uncertainty to outcomes: most mechanisms rely on the behavior of individuals. This motivates me to use firm-level data to study the role of subjective uncertainty and expectations for corporate decisions.

In particular, I conduct a case study focusing on the onset of the COVID-19 crisis. The aim is to empirically examine the theoretical "real options" channel. Its idea is that high uncertainty can make it rational for firms to delay (partially) irreversible investments and to "freeze" hiring. Decision makers "wait and see" until more information is available (Bernanke, 1983; Brennan and Schwartz, 1985; McDonald and Siegel, 1986). In the case of an aggregate downturn, uncertainty increases. At the same time, managers' expectations deteriorate, which may let them defer investments and reduce employment. To better understand the importance of uncertainty and expectations for firm behavior, I exploit the between-firm variation of these perceptions during the COVID-19 shock. I find that firms' decisions to postpone investment projects and to reduce the number of employees are related to first moment changes, but not to changes in uncertainty. While "wait and see" may describe some firms' behavior, the results from averaging over all firms are not in line with the predictions from the "real options" channel.

This paper contributes to several strands of the empirical literature about uncertainty, firms, and business cycles. First, it is part of the literature concerned with the measurement and analysis of subjective business uncertainty. Over the last decade, a handful of surveys have started to elicit the subjective uncertainty of businesses with respect to their own future development. For the US, Altig et al. (2019) have developed the monthly Survey of Business Uncertainty for quantitative one-year ahead expectations and uncertainty regarding a firm's growth of sales, investment, and employment.[2] Respondents are asked for five scenarios from best to worst of the outcome variable. Subsequently, the survey elicits probabilities for these scenarios. Uncertainty is then calculated as a measure of variance of these probability distributions.[3] Bachmann et al. (2018) present an alternative approach for a quarterly supplement to the ifo Business Survey for Germany. They measure subjective uncertainty as the difference between sales growth expectations in the best and in the worst case. Both Altig et al. (2019) and Bachmann et al. (2018) relate uncertainty to past growth and forecast errors at the micro level. I extend this growing strand of literature in three ways. First, I present a new direct and holistic measure of managers' perceived uncertainty. Second, I focus on the relationship between uncertainty and expectations. Third, by considering the business situation, I add a new dimension to the analysis: the relative level position of a firm in its cycle.

Due to the absence of survey-based measures of subjective uncertainty, almost all time-series studies in the literature on uncertainty shocks rely on proxy measures.[4] For a recent comprehensive overview, see Cascaldi-Garcia et al. (2020). A common finding from these time-series measures is that they are counter-cyclical. This paper differs from the literature on proxy measures by presenting aggregate time series of man-

[2] The resulting time series are available online at https://www.frbatlanta.org/research/surveys/business-uncertainty.

[3] Similarly, Bloom et al. (2017) describe quantitative questions on sales growth uncertainty in the Management and Organizational Practices Survey administered by the Census in 2015. For the UK, the Decision Maker Panel also includes questions that follow this methodology (Bloom et al., 2018a).

[4] Popular approaches include indices of implied or realized volatility of stock market returns (Bloom, 2009; Barrero et al., 2017), the cross-sectional dispersion of firm-level outcomes, expectations, or forecast errors (Bachmann and Bayer, 2013, 2014; Bloom et al., 2018b; Bachmann et al., 2013), the conditional volatility of statistical forecast errors from macro time series (Jurado et al., 2015), counts of uncertainty-related keywords in news publications (Baker et al., 2016), and time devoted to uncertainty-related topics in quarterly earnings conference calls (Hassan et al., 2019).

agers' subjective uncertainty about their firms' business development—jointly with their expectations and an assessment of their business situation.[5]

This paper also contributes to the survey-based micro-econometric literature that links the subjective uncertainty of economic decision makers to outcomes. Due to the scarcity of data on subjective uncertainty, the literature for households is small. In a recent contribution, Ben-David et al. (2018) relate households' expectations and subjective uncertainty about their personal income to economic decisions. They find that individuals with more uncertain expectations exhibit more precaution in their consumption and investment behavior.[6] The first contribution concerning firms stems from Guiso and Parigi (1999) who measure the uncertainty of managers about future sales growth. Based on a cross section of Italian firms, they find that businesses with similar expectations about sales growth, but higher uncertainty, invest less.[7] In the same spirit, Dibiasi et al. (2018) study the investment response of a small share of firms that were exposed to an uncertainty-inducing referendum in Switzerland. Their result is that uncertain firms with a high degree of irreversibility lower investment. My analysis during the COVID-19 shock differs from previous work due to the focus on corporate decisions on investment and employment and since I exploit the variation of uncertainty in an aggregate downturn.

Furthermore, this paper is part of the growing literature on uncertainty and expectations during the COVID-19 crisis. For the US and the UK, Altig et al. (2020) and Baker et al. (2020) document large increases in both proxy measures of uncertainty and subjective business uncertainty. Using proxy measures, Baker et al. (2020) estimate that half of the aggregate drop in output can be related to second moment effects. Based on data of the ifo Business Survey, Buchheim et al. (2020a) study corporate mitigation strategies in the face of the COVID-19 shock. They highlight the relation of firms' actions with pre-existing business conditions and with expectations about the duration of the crisis. My analysis differs in that I focus on individual changes of uncertainty and expectations that constitute the aggregate variation in the onset of the COVID-19 recession.

[5] To the best of my knowledge, to date there exists only one study that conducts econometric analyses with an aggregate time series of firms' subjective uncertainty. It is based on an Austrian business survey (Glocker and Hölzl, 2019).

[6] Other household studies that relate measures of subjective uncertainty to outcomes include Guiso et al. 1992, Guiso et al. 2002, and Leduc and Liu 2016.

[7] Bontempi et al. 2010 examine the same relationship for a panel of Italian firms from 1996 to 2004 and show that the relationship between uncertainty and investment varies over time and can become insignificant, which they attribute to changes in the competitive landscape.

My case study that examines firms' "wait and see" behavior is also reminiscent of the literature that studies the impact of uncertainty shocks on the aggregate economy using real business cycle models. As a prominent example, Bloom et al. (2018b) generate drops of 2.5% of GDP with a model that uses nonconvex adjustment costs and the variance of productivity shocks as a measure of risk. Bachmann and Bayer (2013) specifically study the impact of uncertainty on business cycle fluctuations through the "real options" channel. In line with the results from my case study at the onset of the COVID-19 crisis, they find rather small effects.

The paper is structured as follows. Section 2 explains the data and the survey questions. Section 3 compares two measures of perceived uncertainty. Section 4 analyzes the relationship between subjective uncertainty, business expectations, and managers' assessment of the business situation at the micro level. Section 5 presents time series of these variables for the manufacturing sector. Section 6 shows additional time series evidence that also covers the COVID-19 crisis. Moreover, it presents a micro-level case study at the onset of this crisis that relates uncertainty and expectations to corporate decisions about investment and employment.

3.2 Data

This paper is based on data from the monthly ifo Business Survey that currently covers roughly 9,000 German firms. The survey is conducted by the ifo Institute. Data in processible form is available since the German unification in 1990 (since 1980 for West Germany). The sample of firms is maintained to be representative of the German economy. To deal with attrition, ifo adds new respondents to the survey (see Sauer and Wohlrabe 2020). The survey covers firms in manufacturing (IBS-IND, 2020), construction (IBS-CON, 2020), retail and wholesale trade (IBS-TRA, 2020), and services (IBS-SERV, 2020). Its data on the firms' assessment of their business situation and business expectations form the basis of the ifo Business Climate Index, a leading indicator of the German business cycle. As a widely respected measure of business sentiment, it attracts considerable attention from the general public, practitioners, and policy makers. Moreover, ifo Institute is responsible for collecting data according to a set of EU-harmonized business survey questions. They feed into the EU-wide business sentiment index composed by the European Commission.[8]

[8] Aggregate survey results for Germany are presented at www.ifo.de/w/3fvxPxj2P, the harmonized European results, including the European Economic Sentiment Indicator, can be found here: https://ec.europa.eu/info/business-economy-euro/indicators-statistics/economic-databases/business-and-consumer-surveys_en.

A business participating in the survey can be a stand-alone firm or a division of a large conglomerate. The position of the personnel within the firms who fill out the questionnaire is high: Sauer and Wohlrabe (2019) find that more than 90% of the respondents are top-level managers, such as CEOs, CFOs, or department heads. Furthermore, the results from a meta survey from fall 2019 suggest that the respondents within a firm rarely change. Altogether, this ensures very high quality data.

3.2.1 Two Samples for the Micro Analysis

Besides the presentation of aggregate time series, I draw on two main samples of micro data for this paper. The first sample uses data from the manufacturing sector. It starts with the introduction of the direct question for firms' subjective uncertainty in the online part of the survey in July 2017 and ranges until January 2020. In contrast to the other major sectors, namely construction, wholesale and retail trade, and services, the manufacturing sector went through half a business cycle in this period: from a boom in 2017 to a recession that started in the third quarter of 2018. This makes it particularly interesting when studying fluctuations in uncertainty. The main analyses are based on the subsample of manufacturing firms that responded to the online part of the survey, as opposed to paper-based participation. In the sample period, roughly three quarters of all survey participants responded online. This is equivalent to about 1.500 manufacturing firms each month.[9] The manufacturing sample ends in January 2020 to exclude the COVID-19 crisis. I study it in a separate section of this paper.

The second sample is comprised of data from manufacturing, construction, retail and wholesale trade, and services.[10] I use it for a case study at the onset of the COVID-19 crisis. The survey waves of interest range from January to April 2020. The baseline analysis only takes onto account the observations from online participants, but a robustness test also includes other respondents.

[9] Appendix 3.A shows that there are almost no differences between the answers of online participants compared to those who participated paper-based. There is only one notable difference: online participants are more frequently representing large firms (250 or more employees), and somewhat less frequently small firms (less than 50 employees). However, there is no significant difference in the variables capturing the respondents' the assessment of the current business situation and business expectations, which form the core of the analysis in the subsequent sections.

[10] I follow the data cleaning and harmonization procedure described in Link (2020). This involves the assignment of industry codes of the WZ08 classification to all observations and in some cases the aggregation of responses of subsidiaries to the entity level of firms. The German WZ08 classification, short for "Klassifikation der Wirtschaftszweige 2008" is closely related to the European industry classification system NACE Rev. 2.

3.2.2 Survey Questions

The basis for this paper is a novel direct survey question on subjective business uncertainty. I compare the responses of this question to the answers of a second new question on subjective uncertainty. Moreover, I relate them to business expectations and an assessment of the business situation. This section explains the survey methodology and the exact wordings of the relevant questions.

In 2005, ifo introduced a new question design to capture firms' assessment of their current business situation and their expectations for the business development in the subsequent six months. Respondents of the online questionnaires provide their answer by clicking on a visual analogue scale with underlying values that range from 0 to 100.[11] In 2017, ifo started to elicit subjective uncertainty using the same technology. Visual analogue scales are essentially continuous versions of the well-known Likert scales. As such, they are qualitative in nature, and are used, for instance, in medical research to assess feelings and pain intensity (Jensen et al., 2003). Visual analogue scales are easy to understand and, in contrast to trichotomous questions, allow for a differentiated assessment of a respondent's beliefs.

Appendix 3.A shows a screenshot of the original questions regarding the perceived business situation, expectations, and uncertainty from ifo's online questionnaire in the manufacturing survey. Translated into English, the questions are as follows:

1. We assess our current state of business as

   Respondents can click a the visual analogue scale that is labeled "bad" and "good" at its ends, respectively, and "satisfactory" at the center.

2. In the next 6 months, our state of business is likely to

   Respondents can click on a visual analogue scale that is labeled "become rather more unfavorable" and "become rather more favorable" at its ends, respectively, and "roughly stay the same" at the center.

3. We assess the uncertainty w.r.t. our business development in the next 6 months as:

   Respondents can click on a visual analogue scale that is labeled "low" and "high" at its ends, respectively, and "average / usual for the season" at the center.

In addition to eliciting firms' perceived business situation and expectations using visual analogue scales, ifo has continued to apply its more traditional trichotomous

[11] See Stangl (2009) for details on the design and a comparison to the traditional trichotomous questions.

questions for these variables. These traditional questions on the business situation and expectations, in their English translation, read: 1) We assess our current state of business as (a) good (b) satisfactory (c) bad, and 2) Our state of business is likely to (a) become more favourable (b) stay more or less unchanged (c) become less favorable. Question 1) appears in the section with headline "Current situation" and question 2) in the section with headline "Expectations for the next 6 months". I will occasionally use its responses in the subsequent analyses when categorization is helpful.[12]

Following a proposal from the EU Commission's unit for "Economic Situation, Forecasts, Business and Consumer Surveys", ifo implemented a second question regarding uncertainty in April 2019. This question is going to become part of the set of EU-harmonized business survey questions in 2021. Hence, it is going to be available for all countries in the EU. It is based on a similar question included in the business survey of the Austrian Institute of Economic Research, which has been asked in different versions since the 1980s (Glocker and Hölzl, 2019). The second question dealing with uncertainty is part of the survey's section titled "Expectations for the next 6 months". It is asked both online and using paper questionnaires. Translated into English, the question reads:

4. The future development of our business situation is currently

   □ easy to predict

   □ rather easy to predict

   □ rather difficult to predict

   □ difficult to predict

The responses to questions 3 and 4 yield two separate measures of subjective uncertainty. Let *unc* denote the uncertainty measure based on the responses to question 3 and *diff_pred* be the variable that captures the responses to question 4.

3.3 Comparing Two Measures of Subjective Uncertainty

When characterizing and comparing the two measures of uncertainty *unc* and *diff_pred*, we note similarities and differences in the underlying questions. Conceptually, we

[12] The responses to the visual analogue scale questions seem to measure essentially the same as the trichotomous questions: the two unweighted aggregate monthly time series for situation and expectations from 2005 to 2020, respectively, are highly correlated with correlation coefficients of 99% and 86%.

can compare three dimensions. First, any uncertainty measure is characterized by its "object"–the variable over which an individual is uncertain. Second, since uncertainty is forward-looking, the time horizon matters. Third, the way we ask for uncertainty can differ.

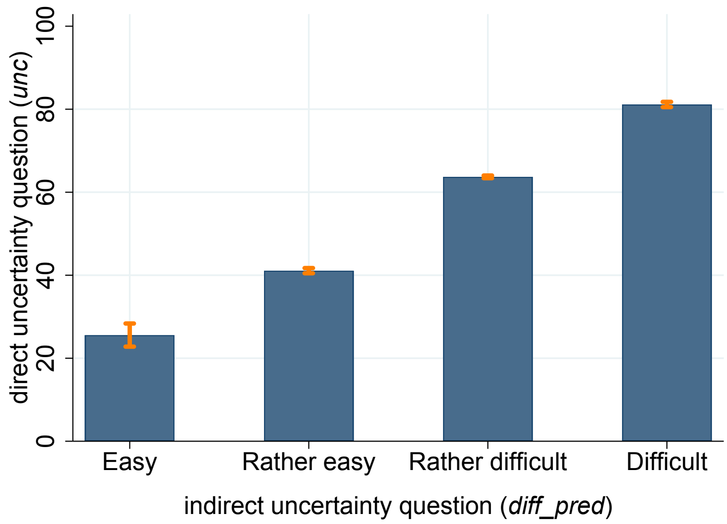
Both *unc* and *diff_pred* have essentially the same object and the same time horizon of uncertainty: the "business development" and the "development of the business situation" over the subsequent six months. The survey deliberately uses the holistic object of "business development". It can be understood as an umbrella term for all relevant firm-specific variables that affect the future path of the business. A meta survey conducted in the fall of 2019 sheds light on the variables that the respondents of the ifo Business Survey consider most important for their assessment of the business situation and expectations. The five factors most important to manufacturing firms are profits, turnover, demand, the stock of orders, and costs (see Appendix 3.B). To further investigate the factors feeding into the holistic measures of business expectations and the business situation, in Appendix 3.B I relate both variables in separate regressions to other variables from the ifo Business Survey. The main findings are that the highest share of the variation of the business situation is explained by the assessments of the profit and order situation, respectively, and by the capacity utilization at the time of the survey. Business expectations are most closely related to production expectations according to the R-squared metric.

Hence, *unc* and *diff_pred* are comprehensive uncertainty measures. By capturing a wide range of aspects in managers' information set, they differ from measures that focus on the uncertainty concerning the development of one particular firm variable, such as sales or employment, as in the surveys presented by Altig et al. (2019) and Bachmann et al. (2018). Advantages of the comprehensive approach are its brevity and universality. A wide range of sources of uncertainty is covered. Moreover, *unc* and *diff_pred* capture both risk and Knightian uncertainty. However, this comes at the cost of a lack of transparency regarding the exact source of the uncertainty.

The main difference between *unc* and *diff_pred*, in addition to the mode of delivery, is the way they ask for uncertainty. Question 3 asks respondents *directly* how uncertain they are, while question 4 asks *indirectly* by inquiring about the degree of difficulty that respondents perceive in predicting the future business development. The responses to the indirect question 4 may either reflect uncertainty as risk, that is, a second moment, or as Knightian uncertainty. In the direct question, it is less clear a priori what respondents think when they are asked for their "uncertainty". Thus, by comparing *unc* and *diff_pred*, I analyze the influence that the type of question has on the responses, and whether managers in firms have a good understanding of the term "uncertainty".

Appendix 3.B presents summary statistics of the variables *unc* and *diff_pred*. Most importantly, I find that *unc* covers the entire range of values between 0 and 100, and that the answer category "rather difficult to predict" is the clear mode of *diff_pred*, while only very few respondents choose the category "easy to predict".[13] Figure 3.1 presents the mean values of the responses from the direct uncertainty question 3, *unc*, for each of the categories of the indirect uncertainty question 4, *diff_pred*. The bar chart is based on the subsample covering the period from April 2019 to January 2020 for which both variables are available.

Figure 3.1: Comparison of two measures of subjective uncertainty



Notes: The figure illustrates the mean values of subjective uncertainty (*unc*), the responses to the direct uncertainty question 3 in Section 3.2.2, for each of the categorical answer options of the indirect uncertainty question 4 (*diff_pred*) in Section 3.2.2 (blue bars). The orange whiskers denote ± 1.96 standard error bands for the mean values.

The main result is that the two variables are almost perfectly aligned: advancement by one category in the perceived difficulty of predicting the future development of the firms' business situation corresponds to a mean of *unc* that is roughly 20 points higher. In other words, the more difficult respondents perceive the prediction of the future development of their business situation, the more uncertain they report to be on the visual analogue scale. Appendix 3.B presents a box plot instead of the bar chart and demonstrates that this finding is robust to using medians instead of means.

The fact that *unc* and *diff_pred* are very similar implies that respondents have a good understanding of the term "uncertainty" when they are directly asked for it. Hence,

[13] One reason for few responses with the category "easy to predict" may be the stylized fact, based on proxy measures, that uncertainty behaves counter-cyclically (Bloom, 2014). In the period for which *diff_pred* is available, namely from April 2019 to January 2020, the manufacturing sector was in a recession. Thus, uncertainty is likely to be above a longer-term average at this time.

a direct question for managers' uncertainty appears to be an easy and sensible way to elicit firms' subjective beliefs. The remainder of the paper focuses on the direct uncertainty measure *unc*. It is available for a longer period of time than *diff_pred*, and it has advantage of being a near-continuous variable. However, I replicate most results using *diff_pred* for robustness.

3.4 Subjective Uncertainty at the Micro Level

Using survey data from businesses allows me to study the properties of uncertainty at the micro level. Moreover, it enables me to study the relationship between perceived uncertainty and expectations from the same respondent. In addition, I can relate subjective uncertainty to the self-assessed business situation of a firm. Given the stylized fact that proxy measures of uncertainty are counter-cyclical, I expect a negative relationship between uncertainty and the business situation. The panel dimension of the sample offers ample variation in the cross section and the time series.

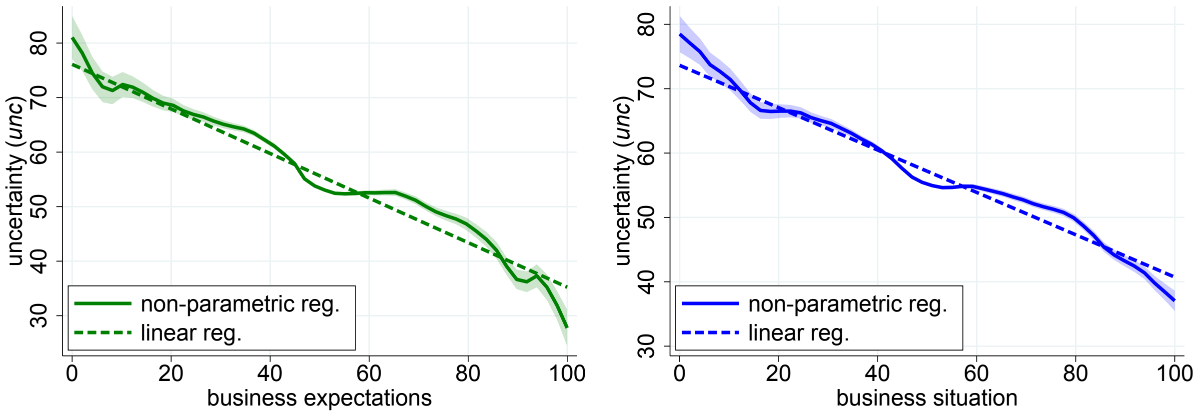
This section has three parts. I start by examining the bivariate relationships between perceived uncertainty vis-à-vis expectations and the business situation, respectively. Second, I study the uncertainty of respondents for combination of these variables. Third, I relate uncertainty to other variables of business activity that are likely to feed into managers' assessment of the business situation and expectations.

3.4.1 Uncertainty vs. Expectations and the Business Situation

Figure 3.1 illustrates two relationships in the pooled sample of manufacturing firms: the relationship between business uncertainty (*unc*) and business expectations in the left plot, and the relationship between business uncertainty (*unc*) and the firms' assessment of their business situation in the right plot. Based on roughly 46,000 firm-time observations, I present non-parametric regression lines and linear fitted lines.

First, I observe a very strong negative and near-linear relationship between subjective uncertainty and expectations. Hence, the more pessimistic respondents are about the development of their business situation over the next six months, the more uncertain they are about it. Moreover, subjective uncertainty is strongly negatively related to the respondents' assessment of the business situation, which indicates the position of a firm in its cycle. Managers perceive higher uncertainty the worse they assess the state of business of their firm. The raw correlations of both relationships in the pooled sample are -0.34.

Figure 3.1: Relation of subjective uncertainty to expectations and the business situation



Notes: This figure shows non-parametric kernel regression lines of degree zero with shaded 95% confidence bands as well as fitted linear regression lines for the relationship between uncertainty (*unc*) and business expectations in the left plot, and between uncertainty (*unc*) and the business situation in the right plot. The non-parametric lines use an epanechnikov kernel and the "rule-of-thumb" bandwidth (Silverman, 1986). The assessment of the business situation, expectations, and uncertainty are based on questions 1, 2, and 3 in Section 3.2.2. Responses are elicited using visual analogue scales that range from 0 to 100, respectively.

I formalize this descriptive evidence by means of regressions. In doing so, I add significance levels and I further check for the asymmetries in high and low expectations and in good and bad business situations. I also specifically examine the within-firm time variation.[14] This can lead to a better understanding of the time variation in aggregate uncertainty, which is at the center of a large body of the literature on uncertainty and business cycle fluctuations.

Table 3.1 presents pooled ordinary least squares regressions of uncertainty (*unc*) on expectations and the business situation. The negative estimates in columns 1 and 2 correspond to the slopes of the linear predicted lines in figure 3.1. Both coefficients are highly significant. If expectations are 10 points lower on the visual analogue scale, uncertainty is 4.1 points higher on average. For a 10 point lower situation, on average, the uncertainty differential is 3.3 points. This captures both the variation between and within firms. The R-squared values of 0.11 and 0.12 in columns 1 and 2, respectively, indicate the presence of ample variation that is not captured by the bivariate relationships.

[14] I note that the visual analogue scale is identical for all firms and, hence, is designed to show time-variation within businesses. However, due to the rather short period of time of the sample of less than three years, some firms might be above or below their longer-run average expectations or their "normal" business situation in most or all of the sample horizon.

Table 3.1: Relation of subjective uncertainty (*unc*) to expectations and the business situation

Dependent variable:	uncertainty (*unc*)				within-firm variation of uncertainty (*unc*)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Business expectations	-0.409***							
	(0.0213)							
Business situation		-0.329***						
		(0.0171)						
Business expectations low			-0.507***					
			(0.0353)					
Business expectations high			-0.323***					
			(0.0348)					
Business situation low				-0.387***				
				(0.0342)				
Business situation high				-0.294***				
				(0.0254)				
Demeaned: business expectations					-0.345***			
					(0.0143)			
Demeaned: business situation						-0.367***		
						(0.0128)		
Demeaned: business expectations low							-0.409***	
							(0.0185)	
Demeaned: business expectations high							-0.273***	
							(0.0177)	
Demeaned: business situation low								-0.401***
								(0.0157)
Demeaned: business situation high								-0.324***
								(0.0156)
Constant	76.10***	73.63***	54.63***	56.48***	0.0155***	0.00397	-0.545***	-0.352***
	(1.103)	(0.950)	(0.338)	(0.345)	(0.00519)	(0.00500)	(0.0918)	(0.0833)
No. of obs.	46394	46413	46394	46413	42802	42809	42802	42809
No. of firms	2598	2601	2598	2601	1766	1765	1766	1765
R-squared	0.11	0.12	0.12	0.12	0.080	0.11	0.081	0.11

Notes: Results from OLS regressions with firm-month observations. The dependent variable in columns 1 to 4 is subjective uncertainty, (*unc*); in columns 5 to 8 it is a variable capturing the within-firm time variation of *unc*. It is constructed as the difference of *unc* from the firm-specific mean of *unc*. The regressors in columns 1 to 4 are based on the responses from questions 1 and 2 in Section 3.2.2. The regressors in columns 5 to 8 are also based on these responses, but capture their within-firm time variation for firms with at least 10 observations. Columns 3 and 4 show results from piecewise regressions with a break at 50 for low and high values of expectations and situation on the visual analogue scale. Columns 7 and 8 present results from piecewise regressions for the demeaned regressors with a break at the firm-specific means, respectively. Standard errors in parentheses, clustered by firm; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

To detect asymmetries, I split the sample into high and low expectations, and into high and low values of the assessment of the business situation. I define numbers on the visual analogue scale of 50 or above as "high" and all others as "'low". In columns 3 and 4, I then regress uncertainty (*unc*) on expectations and the business situation, respectively, using piecewise linear models with a break at 50. Formally,

$$unc_{it} = \alpha_0 + \alpha_1^l x_{i,t}^l + \alpha_1^h x_{i,t}^h + \epsilon_{it},$$

where $x_{i,t}^l = x_{i,t} I(x_{i,t}<50)$, $x_{i,t}^h = x_{i,t} I(x_{i,t} \geq 50)$, $I(\cdot)$ is the indicator function, and $x_{i,t}$ denotes either expectations or the business situation of firm i at time t.

Column 3 demonstrates that the coefficients α_1^l for low and α_1^h for high expectations are both negative and highly significant. Moreover, uncertainty appears to correlate more strongly with low expectations than with high expectations. A Wald test clearly rejects the null hypothesis at the 1%-significance level that the two coefficients are equal. Hence, the relationship between uncertainty and expectations is asymmetric. More unfavorable expectations generally go along with higher uncertainty, but more so for low expectations. Column 4 shows that the coefficients of low and high business situations are both negative and highly significant. While the coefficient of the subsample of bad situations is larger in absolute terms, a Wald test cannot reject the null of equality at the 5%-level (p-value is 0.055). I conclude that a simple linear model captures the relationship between uncertainty and the business situation in the pooled sample with reasonable accuracy.

To isolate the within-firm variation in the panel, I subtract the firm-specific means from the firm-time values of uncertainty, expectations, and the business situation. I do so for a subsample of firms for which at least ten observations are available. More than 92% of the pooled sample remains. Columns 5 and 6 show OLS regressions with these demeaned variables, which produce the same results as fixed effect regressions. Similar to columns 1 and 2, columns 5 and 6 indicate negative and highly significant coefficients for both expectations and the business situation. Magnitudes are also similar.

To examine asymmetries in the within-variation, I define values at or above a firms' mean as "high" and all remaining values as "low". Columns 7 and 8 present results from piecewise linear regressions with the demeaned variables and a break at the firm-specific mean of expectations and the business situation, respectively. Technically, I estimate

$$\widetilde{unc}_{it} = \alpha_0 + \alpha_1^l \tilde{x}_{i,t}^l + \alpha_1^h \tilde{x}_{i,t}^h + \epsilon_{it},$$

where $\tilde{x}^{l}_{i,t} = \tilde{x}_{i,t} I(x_{i,t} < \bar{x}_i)$, $\tilde{x}^{h}_{i,t} = \tilde{x}_{i,t} I(x_{i,t} \geq \bar{x}_i)$, $I(\cdot)$ is again the indicator function, $\bar{x}_i$ is the mean of expectations or the business situation of firm i, and $\tilde{x}_{i,t} = x_{i,t} - \bar{x}_i$ denotes the demeaned expectations or the business situation of firm i at time t. $\widetilde{unc}_{it}$ is the analogously demeaned uncertainty variable.

Column 7 again points to an asymmetry in the relationship between uncertainty and expectation values that are above or below the firm mean. The difference in the coefficients is significant at the 1%-level. For the average firm, an increase in expectations by 10 points above its mean on the visual analogue scale goes along with a decrease in uncertainty by 2.7 points. A decrease in expectations of the same magnitude below the mean coincides with an increase of uncertainty by 4.1 points. Column 8 demonstrates the difference between the coefficients of above average and below average business situations is also statistically highly significant. However, the difference is somewhat smaller than that in expectations.

Based on plots similar to Figure 3.1, Appendix 3.C shows that the stylized facts concerning the negative bivariate relationships between uncertainty and expectations, and between uncertainty and the business situation, also hold for the indirect uncertainty measure *diff_pred*. I conclude that, first, uncertainty is negatively correlated to a firms' cyclical position relative to its trend, which is measured by the business situation. Second, business expectations and the perceived uncertainty regarding these expectations are not only conceptually related. They are also clearly dependent with a negative relationship at the micro level.

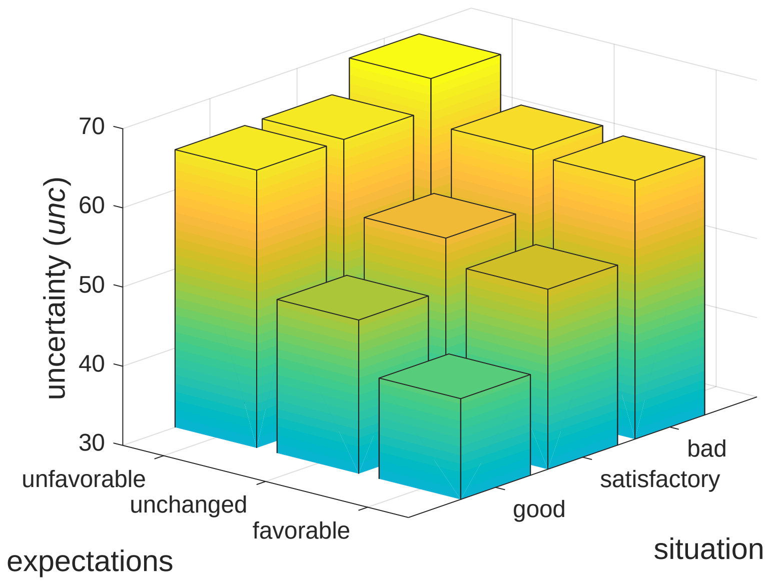
The second finding recalls the stylized fact from the finance literature that conditional volatility is negatively correlated with expected returns at stock markets (see, for instance, Bekaert and Wu 2000 and Hibbert et al. 2008). However, it is unclear a priori whether managers' subjective uncertainty and expectations about their future business behave similarly to financial market outcomes. The new survey evidence suggests that this it indeed the case.

3.4.2 Uncertainty and Combinations of Situation and Expectations

Table 3.1 establishes negative bivariate relationships between uncertainty and business expectations as well as between uncertainty and the business situation. I now take this analysis one step further by asking what degree of uncertainty respondents perceive for combinations of their business situation and expectations. Overall, respondents' expectations and their assessment of the current business situation are positively related. The correlation coefficient is 0.63 in the pooled sample. However, there are numerous cases in which they differ.

Two cases are of particular interest: On the one hand, a firm can be in a good business situation, but its expectations are unfavorable. Is the uncertainty of such a business high, as the negative relationship between the uncertainty and expectations would suggest, or is its uncertainty low, since the business is still in a good situation? On the other hand, a business can be in a poor condition but have positive expectations. Does this go along with high or low subjective uncertainty?

Figure 3.2: Uncertainty by combinations of business situation and expectations



Notes: The bar chart illustrates the mean values of uncertainty (*unc*) by the nine combinations of the categorical responses to the trichotomous questions about the business situation and business expectations. Each mean is based on at least 889 firm-time observations.

Figure 3.2 presents the relationship between uncertainty (*unc*) and combinations of expectations and the business situation. To facilitate the comprehension of this trivariate relationship, I draw on the categorical responses to the trichotomous questions about expectations and the state of business in ifo's business cycle survey. The height of the bars illustrates the mean values of uncertainty for the nine combinations of the business situation assessed as good, satisfactory, or bad, and the expectations reported as favorable, unchanged, or unfavorable. Each combination is based on more than 880 firm-time observations.

The main result is that the respondents perceive high uncertainty if either their expectations are unfavorable or the assessment of their business situation is bad, or both. If expectations are unfavorable, respondents perceive high uncertainty even in a good business situation. If the situation is assessed as poor, uncertainty is high despite favorable expectations. Generally, the relationship between uncertainty and expectations is state-dependent: it is weaker in bad times. Given the bivariate relationships in figure 3.1, it does not come as a surprise that uncertainty is at its lowest if the business situation is good and expectations are favorable.

Appendix 3.C presents results of regressions of uncertainty (*unc*) on dummies for combinations of the categorical business situation and expectations (corresponding to figure 3.2). The case of a good situation and favorable expectations constitutes the baseline. Replicating this estimation using fixed effects allows me to confirm that the main results also hold for the within-firm time variation. Moreover, in Appendix 3.C I demonstrate that the stylized facts regarding the trivariate relationship between uncertainty, expectations, and the business situation are qualitatively the same for the uncertainty measure *diff_pred*.

As an alternative to the three-dimensional bar chart in Figure 3.2, Appendix 3.C presents the trivariate relationship between uncertainty, expectations, and the business situation also in a more continuous version, similar to figure 3.1. Instead of one non-parametric regression line which illustrates the relationship between uncertainty and the business situation, three lines represent the answer options of the trichotomous question about business expectations. Again, it becomes clear that uncertainty is high if expectations are unfavorable, irrespective of the business situation. If expectations are unchanged or favorable, uncertainty is lower the better the situation. An analogous continuous illustration of *diff_pred* instead of *unc* confirms this pattern.

From an aggregate perspective of a stylized business cycle, these micro-level findings tentatively suggest that subjective business uncertainty is elevated from the begin of a downturn to the end of a recovery. In a good state, uncertainty starts to rise early when expectations worsen. In a recession, better expectations do not immediately lower perceived uncertainty. Rather, uncertainty prevails until the situation improves.

What may be reasons for this pattern? A starting point can be the asymmetry of the business cycle (or firm cycle), which implies that the distribution of a firms' growth rates is typically negatively skewed.[15] This implies that firms, in absolute terms, can expect the average negative shock to be larger than the average positive shock. Suppose a firm is in a good business situation and holds unfavorable expectations. Uncertainty perceived as risk then concerns the magnitude of the negative shock. It can be large due to the fat left tail of the demand shock distribution. This could explain why managers are more uncertain if they expect the business situation to deteriorate

[15] Evidence for asymmetry in aggregate and firm-level growth is presented, for instance, by Salgado et al. (2020) and Ilut et al. (2018).

than when they expect an improvement. Orlik and Veldkamp (2014) provide a similar reasoning. They show how tail risks arising from negatively skewed growth rates can explain an increase of a forecasters' macroeconomic uncertainty in recessions.

A complementary intuition for low uncertainty in a good business situation with favorable expectations can be based on strong signals of high demand in that case. Knowledge about orders and being (temporarily) constrained by fix capacities can make it relatively easy for managers to predict future sales and profits.[16] Conversely, in case demand is perceived as weak, decision makers lack knowledge about future sales and profits. Hence, uncertainty is high in the case of unfavorable expectations or in a bad business situation. If an unfavorable business situation is a rather rare event for a firm, managers may also be uncertain since they are unfamiliar with that situation. Uncertainty in a bad situation may also originate from the question whether a realized negative shock is temporary or permanent (Bernanke, 1983). In case of a temporary shock, expectations eventually turn favorable. However, then again the potential magnitude of the expected positive change is large. This can make forecasts quantitatively difficult. High upward risk could explain the empirical finding of high perceived uncertainty in an unfavorable situation with positive expectations. Noisy estimates of the recovery can have the same effect (Van Nieuwerburgh and Veldkamp, 2006). Moreover, in the presence of increased risk aversion in a bad situation, there may be doubts about the reliability of positive demand signals.[17]

3.4.3 Uncertainty and Components of Situation and Expectations

As discussed in Section 3.2.2, the variables of business expectations and business situation are holistic concepts. For the purpose of robustness and traceability, in this section I study whether factors that might feed into these measures correlate with uncertainty in a similar way. Figure 3.3 relates uncertainty to six specific variables of business activity from the ifo Business Survey that reflect the situation and expectations of firms.

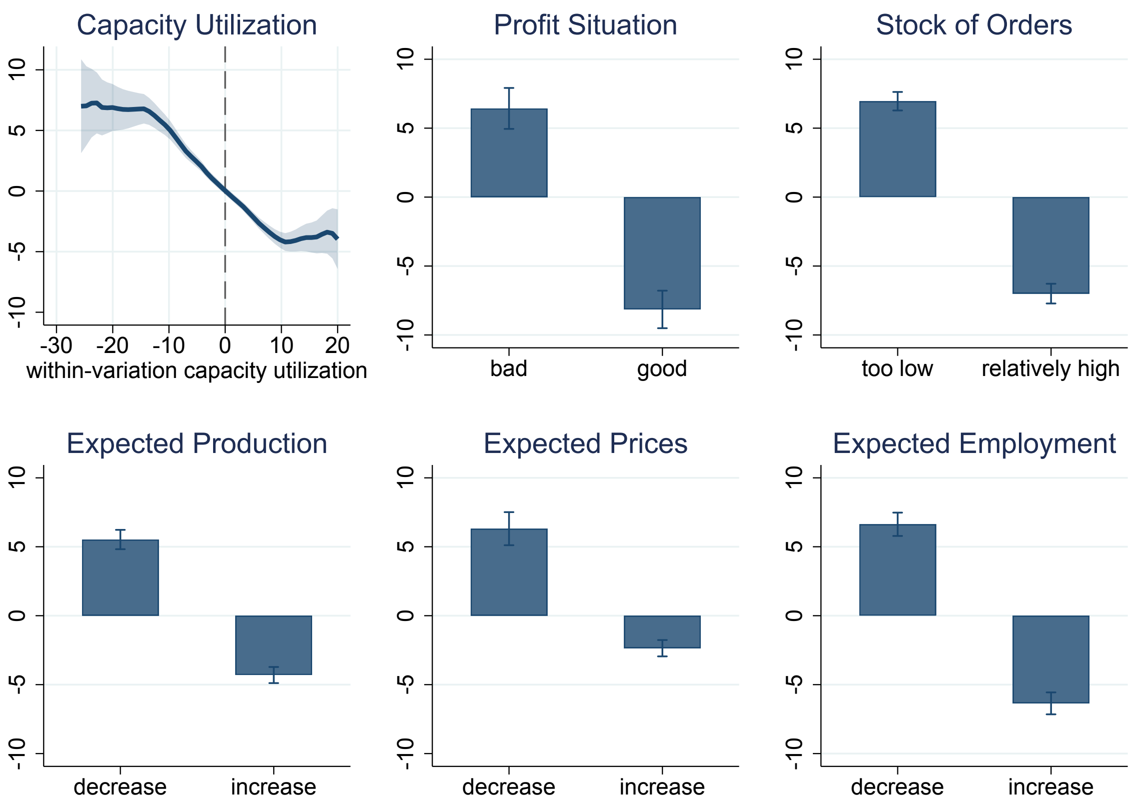
The upper panel of figure 3.3 illustrates measures that are likely to be related to the business situation: capacity utilization in %, the profit situation, and the assessment of the stock of orders. The bottom panel presents expectations about production, prices, and the number of employees of the firm over the next three months. ifo elicits the

[16] In related research, Kuhn and George (2019) provide theoretical evidence that firms' capacity constraints can prevent them from fully exploiting positive demand shocks. They use this rational to explain the asymmetry of business cycles.

[17] Guiso et al. (2018) provide survey evidence that risk aversion was substantially elevated during the period of low activity in 2009, after the shock of the Great Recession.

capacity utilization in a respondent's business at the time of the survey by providing discrete answer options which range from 30% to 100%. The other five variables are based on questions with categorical answer options.

Figure 3.3: Within-variation of uncertainty by variables of business activity



Notes: The top left plot displays a non-parametric kernel regression line of degree zero with shaded 95% confidence bands for the relationship between the within-firm time variation in uncertainty (*unc*) and the within-variation of capacity utilization. The unit at the x-axis is percentage points. I exclude values below the 1%-percentile and above the 99%-percentile for better visibility. The figure further presents bar charts illustrating coefficients from separate fixed effect regressions of uncertainty (*unc*) on categorical variables from the ifo Business Survey, as denoted in the titles of the subplots. In particular, the regressors are dummies based on two categorical answers (labels at the x-axes). Thus, each bar corresponds to a coefficient relative to the middle category, which is "unchanged" in case of all variables except the stock of orders and the profit situation. For the latter two variables, the middle categories are labeled "sufficient" and "satisfactory", respectively. The whiskers at the bars are 95% confidence intervals. Capacity utilization is available once a quarter, the profit situation biannually, and all other variables in monthly frequency.

For capacity utilization, I show a non-parametric regression line in the top left plot. The bars in the other plots correspond to coefficients of fixed effect regressions on dummy variables for the categories indicated on the x-axes, with the middle category serving as the baseline. I focus on the within-firm time variation of uncertainty, but results are similar for the total variation in the pooled sample (see appendix 3.C). The within-variation is indicated at the y-axes of all plots. Technically, I take out firm fixed effects before analyzing the relationships between uncertainty and the firm variables.

I find negative relationships between uncertainty and all six factors. Lower capacity utilization in a firm, a worse profit situation, and a lower stock of orders are all connected to higher uncertainty. A linear regression using fixed effects shows that, on average, a 10 percentage points lower capacity utilization goes along with 3.6 point higher uncertainty on the visual analogue scale. A change in a firm's assessment of its profit situation from "good" to "bad" is associated with an increase of uncertainty of almost 15 points, on average. The discrepancy between a situation with a "too low" and a "relatively high" stock of orders is similar in magnitude. Respondents with less favorable expectations about production, prices, and employment are also more uncertain.

To sum up, I establish robustness of the results in Section 3.4.1 by showing that the negative relationships between uncertainty and expectations, and between uncertainty and the business situation also hold for specific variables that are likely to feed into these holistic measures.

3.5 Subjective Uncertainty in the Aggregate

In this section, I exploit the time series dimension of my sample, which extends over 31 months from July 2017 to January 2020. From an expansionary phase in the second half of 2017, the German manufacturing sector fell into a recession that started in mid 2018 and lasted until the end of the sample period.[18] Hence, the data allows me to study aggregate fluctuations of subjective uncertainty.

Since the Great Recession, many time series of proxy measures of uncertainty have been developed. For a recent overview, see Cascaldi-Garcia et al. (2020). With the new ifo data, however, I am among the first to construct a time series that is based on micro data on subjective uncertainty: it provides information on the uncertainty perceived by actual decision makers in firms.[19] The second key advantage of using survey data about businesses is that I can construct a time series of expectations from the same

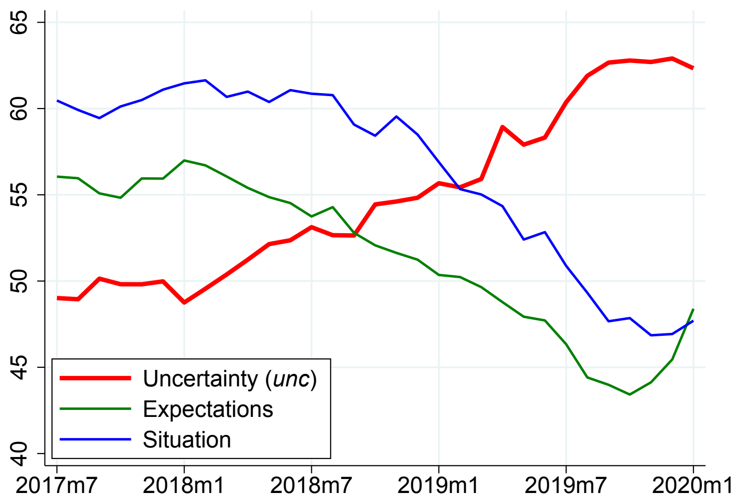
[18] To put this development in context, Appendix 3.D displays a time series of seasonally and calendar adjusted gross value added of the German manufacturing sector for a longer time series, namely since 1999. In the sample period, quarter-on-quarter growth rates dropped from a maximum of 1.7% in Q3 2017 to a minimum of -1.7% in Q2 2019. Annual growth was 3.8%, 1.3%, and -3.4% in 2017, 2018, and 2019, respectively.

[19] Glocker and Hölzl (2019) present a time series of uncertainty for the Austrian economy that is based on micro data. Altig et al. (2019) develop time series of firms' uncertainty and expectations based on firm-level data from the Survey of Business Uncertainty administered by the Federal Reserve Bank of Atlanta. Leduc and Liu (2016) use a time series of the uncertainty of households about purchasing a vehicle.

respondents. This allows me to compare micro-based time series of perceived uncertainty and expectations. Moreover, I relate these series to respondents' assessment of the business situation. Given the micro evidence presented in Section 3.4, I ask whether subjective business uncertainty is negatively related to expectations and the business situation also in the aggregate.

Figure 3.1 presents time series for the manufacturing sector of subjective uncertainty (*unc*) as well as of business expectations and the business situation. They are computed as unweighted averages of the firm-level responses. Appendix 3.D shows that weighting these observations by firm size produces very similar time series and that the average business situation closely follows the two official series of industrial production and gross value added in manufacturing.

Figure 3.1: Time series of subjective uncertainty, expectations, and the business situation



Notes: The figure presents time series of unweighted means of subjective uncertainty, business expectations and an assessment of the respondents' current business situation. These measures are based on the firm-level answers to questions 1, 2, and 3 in Section 3.2.2. The labels at the vertical axis are numbers from a visual analogue scale that ranges from 0 to 100.

The first observation from Figure 3.1 is that firms' subjective uncertainty is countercyclical: uncertainty increases as the assessment of the business situation deteriorates and the manufacturing sector slides into recession in mid-2018. In the short sample, uncertainty and the business situation are highly negatively correlated, with a correlation coefficient of -0.96. This confirms earlier findings based on proxy measures of uncertainty and the time series of subjective business uncertainty for Austria presented by Glocker and Hölzl (2019).

A second, and novel, observation is that the subjective uncertainty of businesses appears to be a mirror image of business expectations for most of the sample period:

when expectations decrease, uncertainty increases, and vice versa. In fact, uncertainty and expectations are almost perfectly negatively correlated (-0.98). Revisiting the stylized fact of countercyclicality, I note that uncertainty already increases in the first half of 2018, that is, *before* the business situation declines. This early increase in uncertainty goes along with a deterioration in expectations. As a third observation, I note that if the situation at the end of the sample period is unfavorable, expectations increase while uncertainty remains essentially unchanged.

The second and third observations imply that the results from the micro level investigation in Section 3.4.2 also seem to hold for the time series: uncertainty is higher when either expectations or the situation are more unfavorable, or both. While the economy is still in a good state, along with deteriorating expectations, uncertainty already increases in the first half of 2018. In the rather bad state at the end of the sample, uncertainty remains at a high level despite an increase in expectations.

Next, I divide the sample into three firm size classes and construct unweighted time series for each of them.[20] The results are displayed in Appendix 3.D. I find that the relationship between uncertainty and expectations as well as the business situation is similar in the aggregate series. In general, the patterns of an increase in uncertainty and deteriorating expectations and business situations between July 2017 and January 2020 are fairly consistent across all size classes.

To analyze whether the aggregate increase in uncertainty is subject to variation across industries in the manufacturing sector, Appendix 3.E presents an analysis of the time variation for subsectors between 2017 and 2019. I find that uncertainty did not rise evenly across industries. In line with the micro evidence and the time series result, uncertainty increased more in industries that experienced a larger decline in expectations and in the business situation.

Is the negative relationship between uncertainty and both expectations and the business situation in the time series specific to the German manufacturing sector and the sample period between July 2017 and January 2020? To broaden the scope of the analysis and to test the validity of the results, I proceed by studying subjective uncertainty and expectations during the COVID-19 crisis.

[20] Based on the number of employees, I define three size classes of firms. Following the definition of the German Federal Statistical Office, small firms have less than 50 employees, medium-sized firms between 50 and 249 employees, and large firms 250 or more employees.

3.6 Case Study: COVID-19 Crisis

The COVID-19 crisis constitutes an unprecedented disruption of economic activity worldwide. Shutdowns imposed by governments triggered severe recessions that unfolded at high speed. These characteristics of the COVID-19 crisis differ considerably from the gradual and rather moderate economic downturn in the German manufacturing sector in Germany in 2018 and 2019. Hence, the COVID-19 crisis provides fertile grounds for testing the robustness of the time series results from the previous section. This constitutes the first part of this case study. In the second part, I exploit cross-sectional differences in changes in managers' uncertainty and expectations at the beginning of crisis to investigate their role for decisions about investment and employment.

3.6.1 Time Series during the COVID-19 Crisis

In this section, I test the robustness of the new stylized facts about the relationship between subjective uncertainty and expectations by extending the sample until July 2020. In this way, I include the COVID-19 crisis. To establish the stylized facts in the first part of the paper, I have focused on data from the manufacturing sector in the time period from July 2017 to January 2020. To analyze time variation in uncertainty, it is most interesting to study. The reason is that, during this time, compared to the other major sectors and the economy overall, the manufacturing sector exhibits the largest fluctuations in economic activity.

With the longer sample that includes the COVID-19 crisis, I present time series for subjective uncertainty (*unc*), expectations, and the business situation for the German economy as a whole. As for all other time series in this section that are based on ifo data, I use the ifo weighting procedure described in Sauer and Wohlrabe (2020) to aggregate firm-level data.[21]

To further test the validity of the stylized facts, I broaden the time series analysis by considering additional measures of subjective business uncertainty. First, I present a monthly time series of *diff_pred* that starts in April 2019.[22] Second, since my previous results could be exclusive to the measures of subjective uncertainty *unc* and *diff_pred*,

[21] Firm-level responses are first aggregated to the 2-digit level of the WZ08 classification using firm size weights, and then aggregated to the level of the total economy by using value added weights from the German Federal Statistical Office.

[22] To compute a balance statistic for *diff_pred*, I assign the values -1, -0.5, 0.5, and 1 for the answer options "easy", "rather easy", "rather difficult", and "difficult", respectively.

I present a quarterly time series of a third measure of subjective uncertainty. It is calculated as the difference between the quantitative quarter-on-quarter sales growth expectations in the best and the worst case in percentage points. The underlying data stems from a survey supplement to the ifo business cycle survey, which is conducted in the first month of a quarter. It also contains a question on expected sales growth in the most likely case. See Bachmann et al. (2018) for a detailed description. This time series is based on ifo survey data from firms in manufacturing, retail and wholesale trade, and services. For all of these sectors, it is available starting in April 2019.

Third, I compare the time series for Germany with time series on subjective uncertainty and expectations for the United States. In particular, I draw on the monthly quantitative survey results on firms' uncertainty and expectations about twelve-month-ahead sales growth from the Federal Reserve Bank of Atlanta. The survey elicits five sales growth scenarios from best to worst in percentage points and asks the respondents to assign probabilities to these scenarios. Uncertainty is computed as the standard deviation and the expectation as the mean of the resulting five-point distribution. The survey design is documented in detail by Altig et al. (2019).[23]

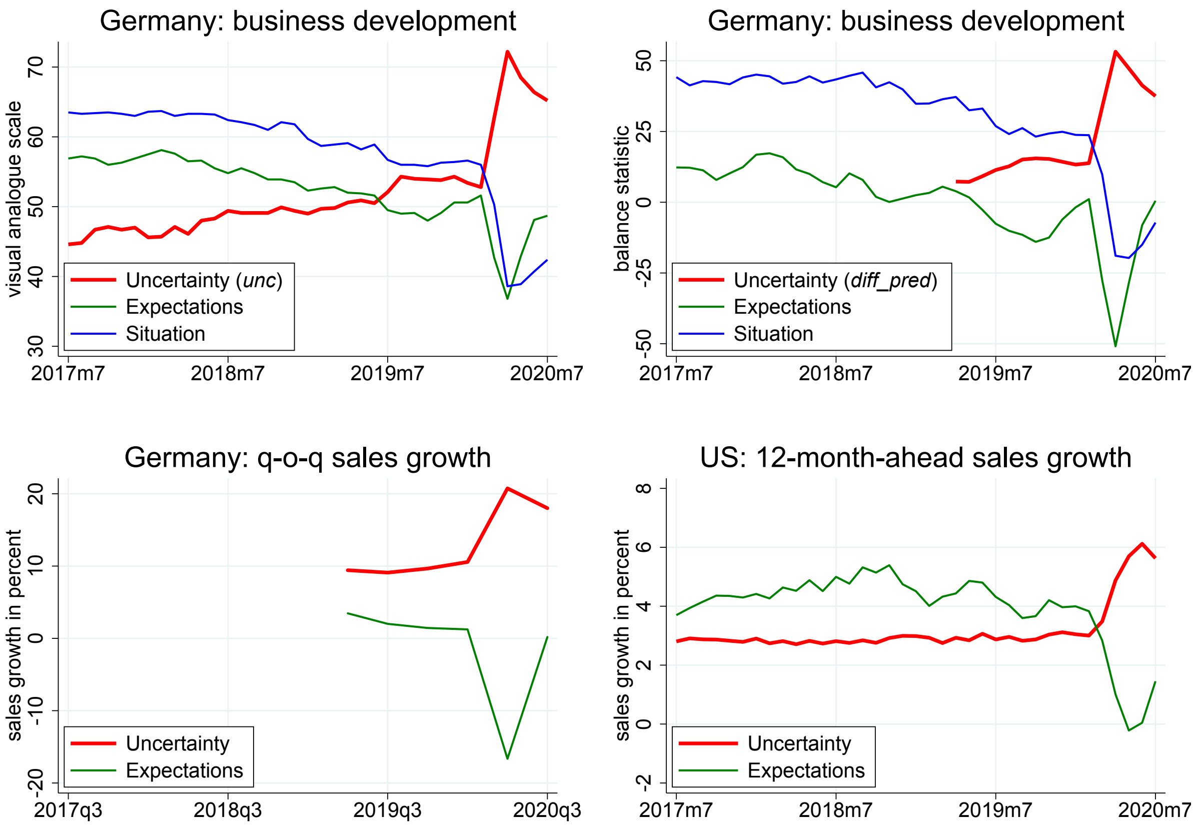
Conceptually, I note that the four measures of uncertainty and expectations differ in several ways: *unc* and *diff_pred* are based on qualitative data and refer to the business development over the next six months, while the other measures are quantitative and refer to quarter-on-quarter and twelve-month-ahead sales growth. The four time series of subjective uncertainty and business expectations are displayed in Figure 3.1. The uncertainty measure *diff_pred* is depicted jointly with the balance statistics from the categorical questions on business expectations and the business situation in the top left plot. In the plots in the top row for *unc* and *unc_pred*, I also include the business situation.

Despite the differences in the construction of the series, the evidence from the four plots is very similar. I make two observations. First, during the COVID-19 crisis the developments of perceived uncertainty and expectations are almost perfectly inversely related. From March 2020 onward, the sharp decline in expectations, followed by a recovery, is mirrored by a sharp increase in uncertainty and a subsequent decrease. Appendix 3.F shows that this pattern is also present for the time series of all major sectors of the German economy. Based on admittedly rather short time series, these findings support the stylized fact of the negative relationship between uncer-

[23] The time series for subjective business uncertainty and expectations of US firms goes back to January 2015 and are available online at https://www.frbatlanta.org/research/surveys/business-uncertainty.

tainty and expectations from the micro data and the time series of the manufacturing sector.

Figure 3.1: Subjective uncertainty and expectations in the COVID-19 crisis and before



Notes: The plot in the top left presents size-weighted time series of subjective uncertainty (*unc*), expectations, and the business situation elicited using visual analogue scales. The uncertainty (*diff_pred*) series in the top right plot is a size-weighted balance statistics constructed from the responses to question 4 described in Section 3.2.2. The other series in the top right plot are balance statistics from ifo's categorical questions on expectations and the business situation described in the same section. The plot in the bottom left shows size-weighted time series of quantitative expectations and uncertainty about q-o-q sales growth. Uncertainty is computed as the difference between best and worst case expectations as described in Bachmann et al. (2018). The data stems from a survey supplement to the ifo business cycle survey and is elicited from firms in manufacturing, wholesale and retail trade, and services. It is available for all of these sectors since Q2 2019. The plot in the bottom right shows business uncertainty and expectations with respect to twelve-month-ahead sales growth from the Atlanta Fed/Chicago Booth/Stanford Survey of Business Uncertainty. For comparability, the x-axis ranges from July 2017 to July 2020 for all plots.

Second, after the COVID-19 spike in April 2020, for all measures the increase in expectations is larger than the decrease in subjective uncertainty. For instance, the top left plot in Figure 3.1 shows that from April to July 2020 business expectations recover 80% of the initial drop from February to April, whereas *unc* only recovers 36%. This difference in the recovery rate is even more pronounced for the series in the other two plots for Germany. While only based on few data points, this second observation supports the previous microdata-based result—and the findings from the time series of the manufacturing sector before the COVID-19 recession—that the relationship between uncertainty and expectations is weaker in bad times. For Germany, low economic activity in mid-2020 is indicated by an unfavorable business situation in the aggregate. At this time, uncertainty remains elevated even though expectations improve.

To sum up, the stylized facts from the micro data and the time series of the manufacturing sector are also manifest during the COVID-19 crisis. They are robust to different measures of perceived uncertainty, they hold for different sectors of the German economy, and they apply both for Germany and the US.

An implication of this finding is that, when using time series econometric analyses, it may be difficult to disentangle possible effects of subjective business uncertainty on macroeconomic variables, such as investment and GDP, from the effects of expectations. As an alternative approach, in the next section I use micro data to empirically study the predictions of a theoretical channel that links uncertainty to firm behavior.

3.6.2 Uncertainty, Expectations, and Corporate Decisions

When examining the effect of uncertainty on firms' economic decisions, one prominent theoretical channel is centered around "real options" (Bernanke, 1983; Brennan and Schwartz, 1985; McDonald and Siegel, 1986).[24] When decisions in firms cannot be easily reversed (or it is costly to do so) and when they affect the profitability of actions taken later, managers confronted with high uncertainty may prefer to "wait and see". More specifically, in such a case, it can be optimal for a business to postpone investment projects and to stop hiring and firing until the outlook becomes clearer. Due to the lack of suitable measures of subjective uncertainty at the firm level, empirical evidence on such behavior is scarce.

Perceived uncertainty seems to fluctuate most around recessions. Section 3.6.1 has provided evidence that the onset of the COVID-19 crisis was accompanied by a massive increase in uncertainty, while expectations plummeted. Based on the theoretical considerations above, in the presence of an uncertainty shock alone I would expect firms to postpone investments and to leave the number of employees largely unchanged.[25]

[24] Other possible theoretical channels include precautionary behavior, borrowing constraints due to higher risk premia, and a loss in confidence caused by ambiguity aversion. Growth options and the Oi-Hartman-Abel effect constitute theoretical mechanisms that can explain positive investment and growth effects from uncertainty. Bloom (2014) provides an overview of these channels.

[25] According to the "real options" channel, uncertainty can lead managers to postpone investments if they are at least partially irreversible. Indeed, Guiso and Parigi (1999) find stronger negative effects of uncertainty on investment the more difficult or costly firms assess the possibility to resell investment goods after they were acquired. Surveying Swiss firms, Dibiasi et al. (2018) present evidence that 70%

A negative first moment shock is also likely to make firms defer investments. However, we would expect them to reduce employment as a consequence. The actual effect of each of the two shocks is unclear. Therefore, it is interesting to use micro data to study the relationship between uncertainty and firms' actions while the aggregate economy simultaneously experiences a first and a second moment shock.

In this case study, I exploit the cross-sectional heterogeneity in changes of subjective uncertainty and expectations between German firms in the onset of the COVID-19 crisis. I use the aggregate variation to find out whether differences in the impact of this shock on the subjective uncertainty of managers relates to differences in their investment and employment decisions.

Sample

To address this question, I use the micro data that underlie the top left plot in figure 3.1 in the previous section. The relevant sample comprises the February, March, and April waves of the ifo Business Survey from 2020 and contains responses from firms in the manufacturing industry, construction, retail and wholesale trade, and the service sector.[26] Based on this data, I relate subjective uncertainty (*unc*) and business expectations in March to subsequent self-reported information in April about whether firms have postponed investment projects and whether they have reduced employment, respectively, because of the COVID-19 crisis. Appendix 3.F contains a translation of the special question in the April wave of the ifo Business Survey which asks firms about measures taken in response to the pandemic.

While the March wave of the ifo Business Survey was conducted from March 2 to March 24, I base my analysis on the subsample of firms that submitted their questionnaires in the nine days from March 16 to March 24.[27] Appendix 3.F shows that this group of respondents is representative for the entire sample of firms that responded in March. Selecting this subsample ensures that managers are well-informed about the gravity of the crisis, and especially about the shutdown. As a result, I can exploit the

of the respondents consider their investments to be highly or fully irreversible; 94% view them as at least somewhat irreversible. The degree of irreversibility seems idiosyncratic to firms as the authors cannot predict it by observable characteristics such as size and sector. Given that almost all firms in the Swiss sample report at least some degree of irreversibility of their investments, I find it reasonable to assume that the "real options" theory would predict that also firms in my sample "wait and see" if they are confronted with high uncertainty.

[26] I follow the data cleaning and harmonization procedure described in Link (2020).

[27] Appendix 3.F presents a histogram of the submission dates in March. Information on this date is missing for 12% of all participants. I exclude these observations from all further analyses. Of the participants for which a submission date is available, 21% responded between March 16 and 24.

full aggregate variation of the shock to uncertainty and expectations. Using data from the beginning of March would blur the within-variation of the aggregate shock as idiosyncratic changes in uncertainty and expectations are likely to dominate changes in beliefs due to the COVID-19 crisis.

Descriptive Evidence

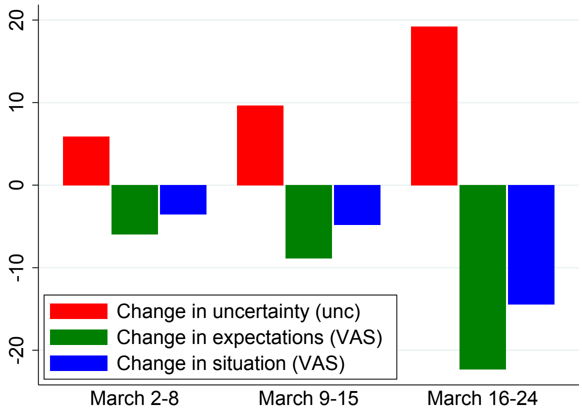
To further motivate why I focus on the firms that responded between March 16 and 24, I present a series of descriptive evidence. Table F.1 in Appendix 3.F presents a short time-line of events during the onset of the COVID-19 crisis in Germany. Due to the unprecedented character of the crisis, the negative consequences of the pandemic for the economy only became apparent gradually: on March 10, many federal states canceled mass events with more than 1,000 participants. On March 13, schools and childcare facilities were closed in most federal states. On March 16, the first day of the subsample period for the analysis, Germany closed its federal borders and the government announced the closing of shops and public facilities.

Along these events, subjective uncertainty (*unc*) increases and business expectations deteriorate.[28] Figure 3.2 divides the respondents of the March wave of the ifo survey into three groups and displays the change of their subjective uncertainty, expectations, and assessment of their business situation against the corresponding values from their responses in February. The first group of respondents who submit their survey responses before March 9, record an increase in uncertainty of 5.9 compared to February. For the second group, with a submission date between March 10 and March 15, it is 9.6 points. The third group, that responds between March 16 and 24, shows the largest increase: on average, these firms report an increase in their perceived uncertainty of 19.2 points on the visual analogue scale. The aggregate increase between February and April 2020 is likewise about 20 points on the visual analogue scale. Hence, by using the responses from the third group of firms, I can exploit the full variation of the aggregate shock. Figure 3.2 further indicates that the decrease in expectations is of a similar magnitude as the increase in uncertainty. The assessments of the current business situation also worsen, but the decline is less than the change in expectations.[29]

[28] Buchheim et al. (2020b) have first documented this shift in firms' expectations and uncertainty.

[29] The month-over-month changes in the three variables for the three weeks of the survey in March 2019 are tiny; they are all smaller than one point on the visual analogue scale in absolute terms. This suggests that there are no shifts in firms' perceptions that regularly occur during the month of March.

Figure 3.2: Changes of uncertainty, expectations, and the business situation in March 2020

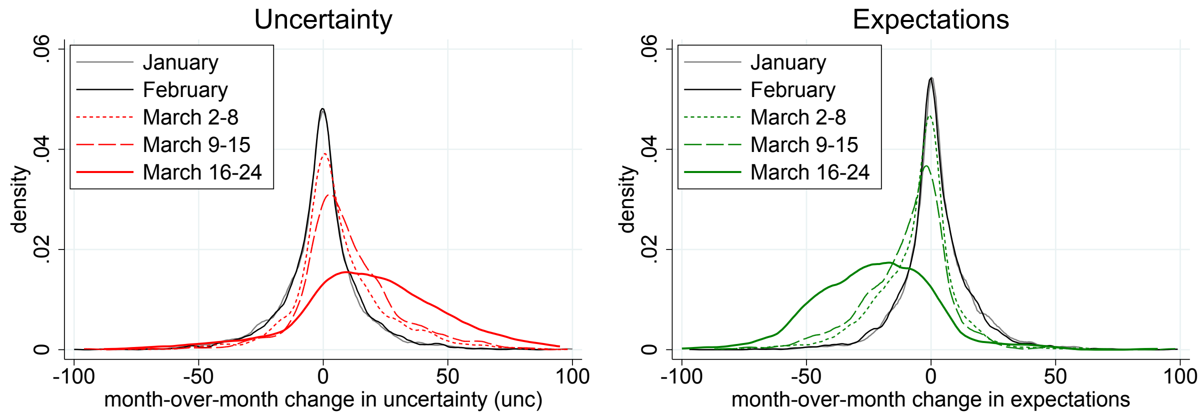


Notes: The figure presents changes in subjective uncertainty (*unc*), business expectations and the business situation between three periods in March 2020 (indicated on the horizontal axis) against the averages of the responses from the same groups of firms in February, respectively. These measures are based on the firm-level answers to questions 1, 2, and 3 in Section 3.2.2. The labels at the vertical axis are numbers from a visual analogue scales that ranges from 0 to 100.

In the analysis, I use the variation between firms with respect to changes in their perceived uncertainty and expectations between February and March. The aim is to capture the variation that is due to the aggregate shock of the COVID-19 crisis, as opposed to idiosyncratic changes. Figure 3.3 presents distributions of changes between February and March in subjective uncertainty (*unc*) and expectations, respectively, for the three groups of firms identified above. The changes for all firms in January and February compared to the previous month, respectively, are also displayed as a reference. They are centered around zero. Thus, these changes are not driven by a common aggregate shock but reflect idiosyncratic variation at a lower level.

While the kernel density estimate for the first group of firms that responded between March 2 and 8 shows only minor deviations from the distributions of the changes in January and February, the kernel density estimates for the second group of firms (March 9-15) differ more. For the third group (March 16-24), the distribution is much wider and clearly positively skewed in case of the changes in uncertainty and negatively skewed for changes in expectations. This reflects the aggregate shock to uncertainty and expectations triggered by the events at the beginning of the COVID-19 crisis. Considering only the third group of firms, that responds between March 16 and 24, should allow me to mostly capture this variation. Moreover, I observe ample heterogeneity between firms: while on average, respondents become more uncertain and pessimistic, these changes in beliefs are more pronounced among some managers compared to others.

Figure 3.3: Distribution of changes in uncertainty and expectations



Notes: The figure shows kernel density estimates for month-over-month changes in subjective uncertainty (*unc*) in the left plot and month-over-month changes of expectations in the right plot for all firms in January and February, respectively, as well as for three groups of firms in March, split by the date of submission of their questionnaire. The density estimates are obtained using an epanechnikov kernel and the "rule-of-thumb" bandwidth (Silverman, 1986). The measures for uncertainty and expectations are based on the responses to questions 1, 2, and 3 in Section 3.2.2. The horizontal axes depict changes based on numbers from visual analogue scales that range from 0 to 100.

Econometric Model and Estimation

I exploit this between-firm variation to estimate the relationship between uncertainty (*unc*) and corporate decisions. As the baseline econometric specification, I choose a probit model of the form:

$$y_{it} = \beta_0 + \beta_1 \Delta u_{i,t-1} + \beta_2 u_{i,t-2} + \beta_3 \Delta e_{i,t-1} + \beta_4 e_{i,t-2} + \beta_3 \Delta s_{i,t-1} + \beta_4 s_{i,t-2} + \gamma' x_i + \epsilon_{it}$$

where y_{it} denotes a dummy variable for firm i's decision at time t, which can be either to postpone investments or to reduce employment. $\Delta u_{i,t-1}$, $\Delta e_{i,t-1}$, and $\Delta s_{i,t-1}$ are changes in uncertainty, expectations, and the business situation between periods $t-2$ and $t-1$. $u_{i,t-2}$, $e_{i,t-2}$, and $s_{i,t-2}$ are the levels of these variables in period $t-2$, respectively. x_i captures time-invariant firm characteristics, namely size and sector, and ϵ_{it} is an error term.

For the estimation, I use survey data from February, March, and April 2020, which refer to $t-2$, $t-1$, and t above. Unconditionally, 43% of the firms that responded between March 16 and 24 report in April that they have postponed investments and 16% state that they have reduced employment because of the COVID-19 crisis.[30] For the baseline regressions, I use the uncertainty measure *unc*, as well as business expectations and situation elicited with a visual analogue scale. These variables are based

[30] The responses of the April survey were collected between April 1 and April 23.

on questions 1, 2, and 3 in Section 3.2.2. To control for the size of the firms, I define dummy variables for three size classes based on the number of employees: small firms have less than 50 employees, medium-sized firms have between 50 and 249 employees, and large firms have 250 or more employees. This categorization is in line with the official definition of the German Federal Statistical Office. To take out sector-specific effects, I include dummies for sectors at the two-digit level of the German WZ08 classification, which is closely related to the European industry classification system NACE Rev. 2.

The econometric model contains both *levels* in period $t-2$ as well as *changes* in uncertainty, expectations, and the business situation between $t-2$ and $t-1$. The levels in February control for heterogeneity between firms before the aggregate shock. This is especially advantageous in view of the boundedness of the visual analogue scale. It allows me to compare changes between firms with the same level in February. As I want to relate changes of uncertainty caused by the aggregate shock of the COVID-19 crisis to managers' investment and employment decisions, my primary focus is on the coefficient of the change in uncertainty, β_1.[31]

Results

Table F.5 presents average marginal effects from ten probit regressions. The dependent variable in columns 1 to 5 is a dummy for firms' decisions to postpone investment, in columns 6 to 10 the dependent variable is a dummy for the decision to reduce employment.

From the regressions in columns 1 to 5, I find that there is a weak positive relationship between changes in uncertainty and the probability that firms postpone investments, when controlling for the base level of uncertainty. However, the coefficients are not significant at the 5%-level and they seem to be dominated by other variables. The level of uncertainty before the aggregate shock of the COVID-19 crisis appears to be a much better predictor of firms' decisions to postpone investments. Column 2 shows that, unconditionally, both the base level and the change in expectations are strongly

[31] Given the negative relationships of uncertainty and expectations as well as uncertainty and the business situation documented in Section 3.4.1, there might be a concern of multicollinearity. Table F.3 in Appendix 3.F shows that the main regressors in levels and changes are indeed correlated. However, none of the pairwise correlation coefficients exceeds 0.53. The R-squared from an OLS regression of $\Delta u_{i,t-1}$ on the level of uncertainty in $t-2$, as well as level and change variables of expectations and the business situation is 0.33. This leaves room for independent contributions of the regressors. Table F.3 also shows that individual firms seem to experience the aggregate uncertainty and expectation shocks quite differently: the correlation between changes in uncertainty and changes in expectations is merely -0.21.

negatively related to the dependent variable. The coefficients are quantitatively important: a decrease in expectations by ten points on the visual analogue scale goes along with an increase of the likelihood to postpone investments by roughly five percentage points. In the joint regression of levels and changes in uncertainty and expectations in column 3, the level of expectations becomes insignificant. When adding variables for the level and change of the business situation in column 4, only the change in the situation is significant. These results are robust to including firm size and sector dummies in column 5. To sum up, changes in expectations and the business situation triggered by the COVID-19 crisis are related to a higher likelihood to postpone investments, while changes in uncertainty are not. Moreover, firms with a higher level of uncertainty before the aggregate shock more often defer investments because of the crisis.

Columns 6 to 10 show that changes in uncertainty are not related to the decision to lay off employees. In case of a "freeze" of employment, I would have expected a significant negative coefficient. With higher uncertainty, firms would be less likely to lay off personnel. However, the coefficients in all specifications are quantitatively small and statistically not significant. In contrast, column 7 illustrates that the relationship between changes in expectations and the decision to reduce employment is strong. The more pronounced the deterioration in expectations, the more likely respondents downsize their workforce. The levels of uncertainty and expectations in February in columns 6 and 7 are also connected to a higher probability to lay off employees. In the joint regression in column 8, the level and change in expectations drive out the level of uncertainty. Including levels and changes in the business situation in column 9, as well as size and sector dummies in column 10, emphasizes the role of pre-existing differences between firms for their decisions to lay off staff. Moreover, changes in the business situation seem most important as a transmission channel from the aggregate shock to the decision to reduce employment.

These results suggest that the first moment shock at the onset of the COVID-19 crisis dominates the effects that we expect from a pure uncertainty shock. I do not find evidence that firms postpone investment or "freeze" employment following changes in uncertainty. In contrast, negative changes of expectations and of the assessment of the business situation are significantly related to these corporate decisions. Moreover, perceptions and the business situation before the aggregate shock also predict firms' reactions to the crisis. This is in line with previous findings by Buchheim et al. (2020a).

Table 3.1: Relationship between corporate investment and employment decisions and past uncertainty, expectations, and situation

Dependent variable:	decision: postponement of investment					decision: reduction of the number of employees				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
ΔUncertainty in $t-1$	0.00150*		0.000543	0.000631	0.000583	0.0000985		-0.000411	-0.000279	0.000278
	(1.84)		(0.67)	(0.77)	(0.71)	(0.15)		(-0.67)	(-0.46)	(0.45)
Uncertainty in $t-2$	0.00552***		0.00459***	0.00456***	0.00406***	0.00208***		0.000654	0.000679	0.00100
	(5.82)		(4.54)	(4.27)	(3.73)	(2.60)		(0.85)	(0.87)	(1.16)
ΔExpectations in $t-1$		-0.00534***	-0.00466***	-0.00312***	-0.00330***		-0.00325***	-0.00311***	-0.00147*	-0.00109
		(-5.93)	(-4.89)	(-2.96)	(-3.15)		(-3.88)	(-3.66)	(-1.77)	(-1.39)
Expectations in $t-2$		-0.00433***	-0.00216	-0.000945	-0.000599		-0.00568***	-0.00524***	-0.00374***	-0.00402***
		(-3.44)	(-1.60)	(-0.64)	(-0.40)		(-5.33)	(-4.74)	(-3.20)	(-3.23)
ΔSituation in $t-1$				-0.00330***	-0.00331***				-0.00315***	-0.00286***
				(-3.31)	(-3.14)				(-4.09)	(-3.75)
Situation in $t-2$				-0.00210*	-0.00166				-0.00214**	-0.00163*
				(-1.76)	(-1.29)				(-2.47)	(-1.69)
Dummy medium sized firms					0.0309					0.0305
					(0.71)					(0.86)
Dummy large firms					0.0279					0.0284
					(0.48)					(0.64)
Sector dummies					YES					YES
No. of firms	660	667	656	653	630	660	667	656	653	561
Pseudo R-sq.	0.037	0.039	0.066	0.078	0.15	0.019	0.077	0.080	0.11	0.24

Notes: Average marginal effects from probit regressions. The dependent variable in columns 1 to 5 is a dummy for the decision to postpone investment projects because of the COVID-19 crisis, in columns 6 to 10 it is a dummy for the decision to reduce employment because of the COVID-19 crisis. Information on these corporate decisions stems from the ifo Business Survey in April 2020. The regressors are levels of uncertainty (*unc*), expectations, and business situation from February 2020, and month-over-month changes from March 2020. These measures are based on the responses to questions 1, 2, and 3 in Section 3.2.2. t-statistics in parentheses; * p < 0.10, ** p < 0.05, *** p < 0.01.

Appendix 3.F presents additional regressions for two related managerial decisions: the cancellation of investment projects and the implementation of short-time work. I use dummies for these actions as dependent variables in otherwise unchanged regressions. The data stems from the same special question in April as the data on the decisions to postpone investments and to reduce employment. Unconditionally, 19% of the firms that responded between March 16 and 24 report to have canceled investment projects, and 49% indicate to have introduced short-time work. In principal, uncertainty could also affect these decisions via precautionary behavior. However, this does not seem to be the case: once expectations are controlled for, again I find that only first moment changes—and pre-existing business conditions before the aggregate shock—are related to these investment and employment decisions.

Robustness

Did managers anticipate the economic consequences of the COVID-19 crisis before March 2020? News about the COVID-19 epidemic in Asia could have affected uncertainty and expectations of respondents in February. However, Buchheim et al. (2020b) show that there was basically no such effect. Instead, respondents of the ifo Business Survey only changed their beliefs once domestic policy imposed measures to contain the epidemic in March. The spread of the disease in Italy only became known on February 21, the last day of this month's survey wave. Hence, information about the outbreak in Europe is also unlikely to affect the results.

Appendix 3.F presents several robustness checks for the baseline regression results above. First, instead of computing marginal effects from probit regressions, I estimate linear probability models. The results are almost exactly the same. Second, I estimate the baseline regressions excluding firms from the manufacturing sector. Due to the relatively poor performance of this sector relative to the other major sectors before the COVID-19 crisis, it may drive some of the results. However, this is not the case: the main regressions results are robust to excluding manufacturing firms from the sample.

Third, to account for possible measurement error in the variables for uncertainty, expectations, and the business situation, I apply the Obviously Related Instrumental Variable (ORIV) approach proposed by Gillen et al. (2019). To this end, in the sample from February to April 2020, I first regress the uncertainty variable *unc* on *diff_pred* and use the predicted values, as well as changes of the predicted values, as alternative regressors $\Delta u_{i,t-1}*$ and $u_{i,t-2}*$. These new variables capture the common variation in *unc* and *diff_pred* and are free of independent and identically distributed measurement error. By regressing expectations and the business situation measured using visual analogue scales on their categorical counter-parts, I analogously obtain predicted values for these variables, in levels and in changes. Table F.7 in Appendix 3.F shows that the main results are robust to re-estimating the baseline regressions with these modified variables. A difference is that the coefficients of expectations and the business situation are substantially larger using the ORIV approach. This suggests the presence of an attenuation bias in the baseline regressions. As a consequence, in the regressions with the modified variables, uncertainty in February is driven out by expectations and the situation. In contrast to the baseline regressions, using the ORIV approach the level of uncertainty before the aggregate shock does not predict firms' investment and employment decisions anymore.

As another robustness test, Table F.8 replicates the baseline regressions in Table F.5 using the uncertainty measure *diff_pred* as well as the categorical variables for expectations and the business situation. This requires the definition of several dummy variables. Regarding *diff_pred*, I join the sparsely populated category "Easy" with the category "Rather easy" and create indicator variables for the resulting three levels of the difficulty to predict the future business development in periods $t-2$ and $t-1$. Based on these uncertainty states, I define dummy variables for positive and negative changes from $t-2$ to $t-1$. Moreover, I use the trichotomous variables on expectations and the business situation to create dummies for the levels in $t-2$ as well as positive and negative changes between $t-2$ and $t-1$, respectively. In the regressions, I define the lowest uncertainty level as well as the middle categories of expectations and the business situation as the baseline. The baseline for the variables in changes are the cases of no change, respectively.

The regression results in Table F.8 confirm the main findings from above. Unfavorable expectations in the level as well as negative changes in expectations drive out the effect captured by the dummy for increases in uncertainty. This holds true for both the decision to postpone investments and the decision to reduce the number of employees. In regressions with only uncertainty and expectation variables, the level of uncertainty in February is also significantly related to the outcome dummies. However, it turns insignificant once I control for levels and changes of the business situation.

3.7 Conclusion

The uncertainty of firms and households is inherently subjective. As for expectations, a good way to measure it is to ask actual decision makers about their perceptions. Based on data from a large and representative German business survey, this paper presents a novel direct measure of firms' subjective uncertainty about the development of their businesses. It appears to be a sensible measure since it contains essentially the same information as a second measure of perceived uncertainty that asks managers to assess the difficulty to predict their future business development. The collection of more data of this kind can facilitate research concerned with the effect of subjective uncertainty on decision making and the business cycle.

While conceptually closely related, there is little empirical evidence on the relationship between subjective uncertainty and expectations. I contrast managers' perceived uncertainty with their business expectations and an assessment of their business situation and find strong negative relations at the micro level and almost perfectly inverse relationships in the time series. Moreover, the relationship between uncertainty and expectations is state-dependent: in bad times, this relationship is weaker, since uncertainty is generally high. The new evidence highlights the simultaneity of movements in subjective uncertainty and both expectations and business activity in the aggregate. This impedes the identification of aggregate uncertainty shocks using time-series econometric methods. As an alternative approach, the availability of micro data of managers' perceptions allows me to analyze the impact of uncertainty on firm behavior.

Exploiting the between-firm variation at the onset of the COVID-19 crisis, I investigate the relation of uncertainty and expectations to firms' decisions to postpone investment projects and to reduce the number of employees. I find that changes in uncertainty during the aggregate downturn do not predict "wait and see" behavior. By contrast, first moment changes are related to the deferral of investment and a reduction of the workforce. These results may be particular to the sharp economic downturn in March 2020, which was extraordinary in many respects. More research should be devoted to examine the link between perceived uncertainty and corporate actions. Of particular interest could be the business cycle stage of an early recovery, when expectations improve but uncertainty remains elevated.

Appendix

3.A Data

Figure A.1: Online questionnaire with questions using visual analogue scales

Notes: In the original German, the screenshot shows the section of the online survey questionnaire that elicits an assessment of the business situation as well as expectations and subjective uncertainty about the future business development using visual analogue scales. They correspond to questions 1, 2, and 3 in Section 3.2.2.

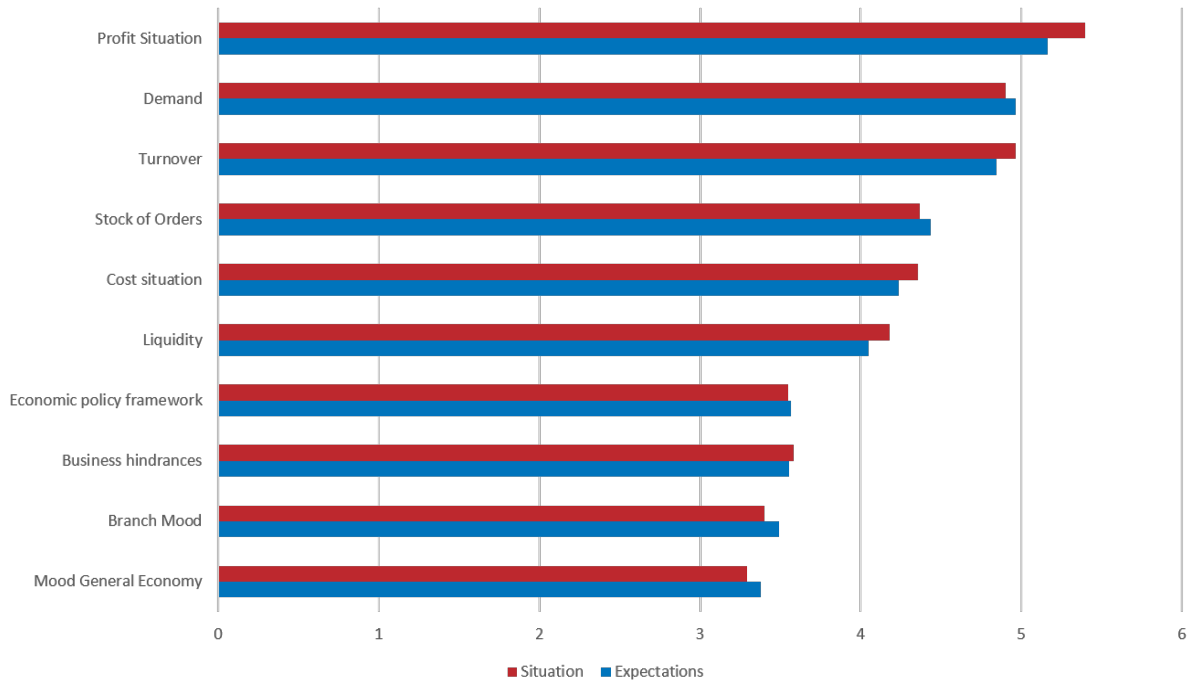
Table A.1: Representativeness of online participants in the ifo Business Survey

Dep. variable: dummy for online participation	(1) probit
Dummy medium sized firms	0.0177
	(0.0455)
Dummy large firms	0.250***
	(0.0591)
capacity utilization in %	0.0107***
	(0.00171)
Dummy production vs previous month: more	0.00133
	(0.0409)
Dummy production vs previous month: less	0.0996**
	(0.0431)
Dummy production vs previous month: no production	-0.101
	(0.239)
Dummy order vs previous month: higher	0.0405
	(0.0428)
Dummy order vs previous month: lower	0.0266
	(0.0418)
Dummy demand vs previous month: higher	0.113***
	(0.0431)
Dummy demand vs previous month: lower	0.0287
	(0.0406)
Dummy domestic prices vs previous month: increase	-0.0107
	(0.0418)
Dummy domestic prices vs previous month: decrease	-0.158*
	(0.0804)
Dummy capacity utilization, appraisal: more than enough	-0.0580
	(0.0582)
Dummy capacity utilization, appraisal: not enough	0.0564
	(0.0481)
Dummy state of business: good	-0.0330
	(0.0454)
Dummy state of business: bad	0.0680
	(0.0598)
Dummy expected commercial operations: favourable	0.0404
	(0.0435)
Dummy expected commercial operations: unfavourable	-0.00589
	(0.0428)
Dummy orders, appraisal: relatively high	-0.0433
	(0.0529)
Dummy orders, appraisal: too small	0.0924*
	(0.0550)
Dummy foreign orders, appraisal: relatively high	-0.0271
	(0.0643)
Dummy foreign orders, appraisal: too small	-0.0382
	(0.0611)
Dummy foreign orders, appraisal: no fexport	-0.372***
	(0.0689)
Dummy expected domestic prices: increase	0.000872
	(0.0387)
Dummy expected domestic prices: decrease	0.0599
	(0.0691)
Dummy expected number of employees: increase	0.0171
	(0.0520)
Dummy expected number of employees: decrease	0.0184
	(0.0528)
Dummy stock of inventories: too little	0.0141
	(0.0705)
Dummy stock of inventories: too much	0.0272
	(0.0578)
Dummy stock of inventories: no stock-keeping	0.103*
	(0.0584)
Dummy constraints to production: yes	0.196***
	(0.0423)
Constant	-0.444***
	(0.154)
No. of observations	17432
No. of firms	3182
Pseudo R-squared	0.035

Notes: Probit regression of a dummy variable that identifies online participants—vs. mainly paper-based respondents—in the manufacturing part of the ifo Business Survey on firm characteristics and variables of business activity. The underlying sample spans from July 2017 to January 2020. Standard errors in parentheses, clustered by firm; * p < 0.10, ** p < 0.05, *** p < 0.01.

3.B Comparing Two Measures of Subjective Uncertainty

Figure B.1: Determinants of business situation and expectations from meta survey



Notes: The bar chart presents the results of two questions in a meta survey about the ifo Business Survey conducted in fall 2019. Respondents were asked to rate the importance of a list of variables for their assessment of the business situation and business expectations using numbers from 0 (unimportant) to 6 (very important).

Table B.1: Relationship of the business situation and variables of business activity

Dependent variable: business situation	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Dummy production vs previous month: more	11.13***										
	(23.00)										
Dummy production vs previous month: less	-18.44***										
	(-38.73)										
Dummy orders vs previous month: higher		9.808***									
		(22.50)									
Dummy orders vs previous month: lower		-14.89***									
		(-34.39)									
Dummy demand vs previous month: higher			7.155***								
			(16.27)								
Dummy demand vs previous month: lower			-14.76***								
			(-33.05)								
Dummy domestic prices vs previous month: increase				7.367***							
				(12.33)							
Dummy domestic prices vs previous month: decrease				-16.43***							
				(-16.36)							
capacity utilization in %					0.715***						
					(29.89)						
Dummy stock of orders: relatively high						16.83***					
						(33.03)					
Dummy stock of orders: too small						-22.36***					
						(-44.99)					
Dummy profit situation: good							19.56***				
							(33.77)				
Dummy profit situation: bad							-19.48***				
							(-31.01)				
Dummy constraints to production: yes								-7.509***			
								(-12.64)			
Dummy expected production: increase									8.280***		
									(15.19)		
Dummy expected production: decrease									-16.73***		
									(-31.46)		
Dummy expected number of employees: increase										15.80***	
										(25.95)	
Dummy expected number of employees: decrease										-19.63***	
										(-31.22)	
Dummy expected domestic prices: increase											5.618***
											(10.16)
Dummy expected domestic prices: decrease											-15.43***
											(-17.04)
Constant	57.16***	57.19***	57.48***	55.90***	-3.934*	57.79***	54.24***	60.14***	56.73***	56.18***	55.92***
	(158.70)	(154.63)	(148.05)	(149.99)	(-1.91)	(187.26)	(159.97)	(146.06)	(154.77)	(158.23)	(148.54)
No. of observations	46006	45938	46056	45941	14492	45597	7222	16060	46127	46026	45852
R-squared	0.18	0.17	0.13	0.045	0.25	0.43	0.45	0.032	0.13	0.19	0.044

Notes: Results from OLS regressions. The dependent variable is the respondents' assessment of the business situation, based on question 1 in Section 3.2.2. The base category of the dummy variables constructed from the responses of the questions on changes in production, orders, demand, and prices, and of the expectations questions is "unchanged". The base level for the dummies for the stock of orders and profit situation is labeled "satisfactory", respectively. t-statistics in parenthesis. Standard errors are clustered by firm; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.2: Relationship of business expectations and variables of business activity

Dependent variable: business expectations	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Dummy production vs previous month: more	8.363***										
	(20.17)										
Dummy production vs previous month: less	-9.860***										
	(-22.29)										
Dummy orders vs previous month: higher		7.653***									
		(21.29)									
Dummy orders vs previous month: lower		-10.63***									
		(-29.02)									
Dummy demand vs previous month: higher			7.541***								
			(20.88)								
Dummy demand vs previous month: lower			-11.00***								
			(-29.67)								
Dummy domestic prices vs previous month: increase				5.005***							
				(11.28)							
Dummy domestic prices vs previous month: decrease				-11.31***							
				(-12.47)							
capacity utilization in %					0.254***						
					(13.44)						
Dummy stock of orders: relatively high						6.068***					
						(12.95)					
Dummy stock of orders: too small						-11.29***					
						(-24.93)					
Dummy profit situation: good							6.832***				
							(12.39)				
Dummy profit situation: bad							-8.582***				
							(-13.94)				
Dummy constraints to production: yes								-4.411***			
								(-10.22)			
Dummy expected production: increase									11.62***		
									(27.39)		
Dummy expected production: decrease									-15.81***		
									(-35.93)		
Dummy expected number of employees: increase										11.47***	
										(21.06)	
Dummy expected number of employees: decrease										-13.29***	
										(-23.26)	
Dummy expected domestic prices: increase											4.808***
											(10.97)
Dummy expected domestic prices: decrease											-13.35***
											(-17.49)
Constant	51.31***	51.81***	51.71***	51.07***	30.15***	52.60***	50.63***	53.61***	50.96***	51.15***	51.05***
	(209.07)	(208.25)	(209.68)	(189.94)	(18.38)	(202.73)	(155.89)	(168.91)	(228.92)	(210.63)	(193.40)
No. of observations	45989	45923	46039	45927	14488	45575	7219	16053	46111	46011	45841
R-squared	0.11	0.14	0.14	0.033	0.052	0.14	0.11	0.018	0.24	0.14	0.052

Notes: Results from OLS regressions. The dependent variable is business expectations, based on question 2 in Section 3.2.2. The base category of the dummy variables constructed from the responses of the questions on changes in production, orders, demand, and prices, and of the expectations questions is "unchanged". The base level for the dummies for the stock of orders and profit situation is labeled "satisfactory", respectively. t-statistics in parenthesis. Standard errors are clustered by firm; * p < 0.10, ** p < 0.05, *** p < 0.01.

Table B.3: Summary statistics of situation, expectations, and uncertainty (*unc*)

Variable	No. Obs	Mean	Std. Dev.	P1	P10	P25	P50	P75	P90	P99
Business situation	46413	56.1	20.7	6	30	45	53	71	85	99
Business expectations	46394	51.2	16.5	8	30	45	50	59	73	95
Uncertainty: *unc*	46740	55.2	19.9	5	28	47	53	69	81	97

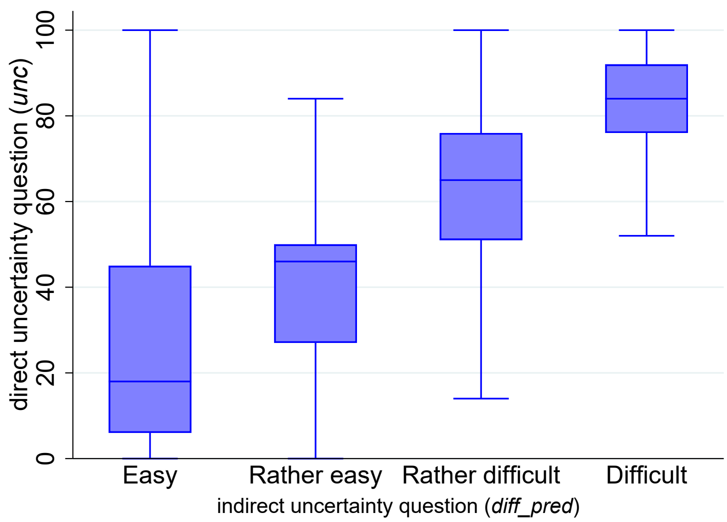
Notes: Summary statistics of the responses from questions 1, 2, and 3 in section 3.2.2 for the manufacturing sector. The sample ranges from July 2017 to January 2020.

Table B.4: Summary statistics of uncertainty: *diff_pred*

	No. Obs.	Share
Easy	277	0.02
Rather easy	3,282	0.20
Rather difficult	10,053	0.62
Difficult	2,499	0.16
Total	16,111	1.00

Notes: Distribution of the responses to question 4 in section 3.2.2 for the manufacturing sector. The sample ranges from April 2019 to January 2020.

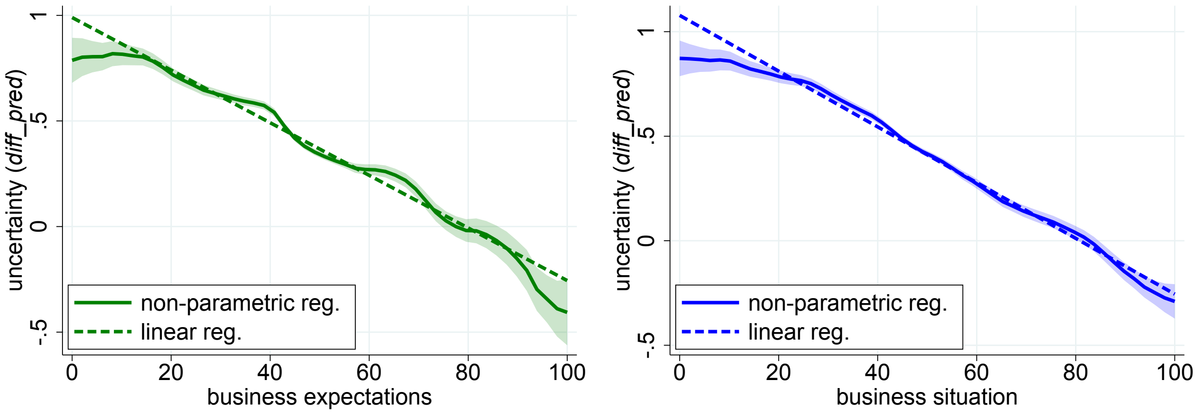
Figure B.2: Comparison of two measures of subjective uncertainty



Notes: The box plot illustrates the distribution of the responses of the direct uncertainty question 3 in Section 3.2.2 (*unc*) for each of the answer options of the indirect uncertainty question 4 (*diff_pred*).

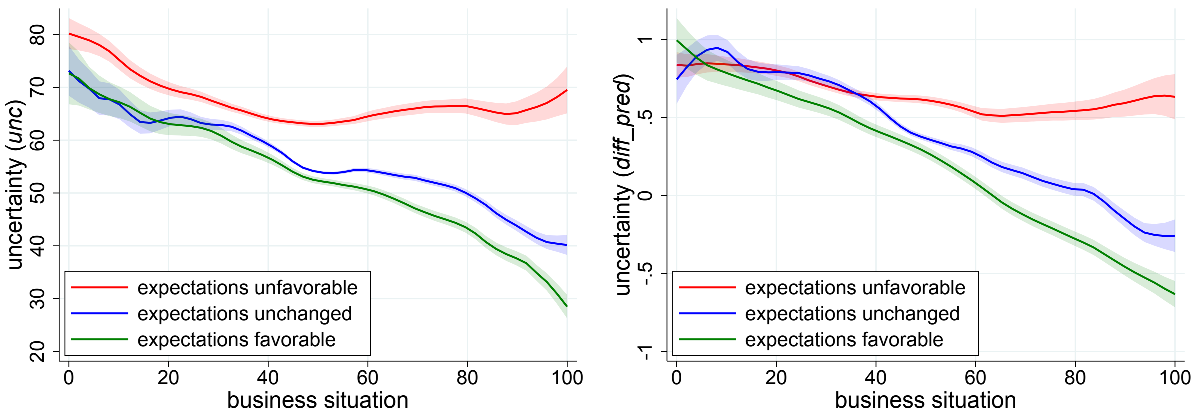
3.C Subjective Uncertainty at the Micro Level

Figure C.1: Relation of uncertainty (*diff_pred*) to expectations and the business situation



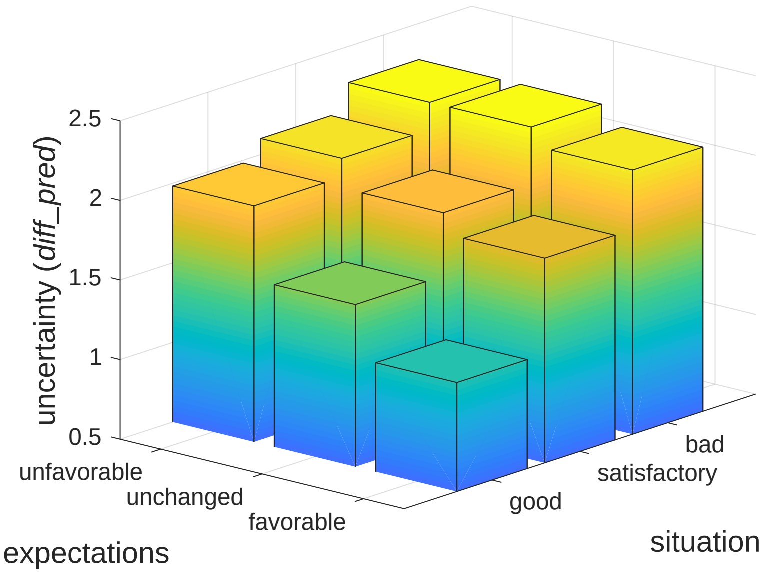
Notes: This figure shows non-parametric kernel regression lines of degree zero with shaded 95% confidence bands as well as fitted linear regression lines for the relationship between uncertainty (*diff_pred*) and business expectations in the left plot, and between uncertainty (*diff_pred*) and the business situation in the right plot. The assessment of the business situation, expectations, and uncertainty are based on questions 1, 2, and 4 in section 3.2.2, respectively. The categorical values of diff_pred “Easy”, “Rather Easy”, “Rather difficult”, and “Difficult” are coded as -1.5, -0.5, 0.5, and 1.5, respectively.

Figure C.2: Relation of uncertainty to the business situation by expectation category



Notes: The figure shows two plots with non-parametric kernel regression lines of degree zero with shaded 95% confidence bands for the relationship between uncertainty and the business situation, for three subsamples according to the respondents’ business expectations being unfavorable, unchanged, and favorable. The vertical axis of the left plot depicts the uncertainty measure *unc* that is based on question 3 in Section 3.2.2; for the right plot it is *diff_pred* that is based on question 4 in Section 3.2.2. The assessment of the business situation is based on question 1 in Section 3.2.2. The categorical values of *diff_pred* “Easy”, “Rather Easy”, “Rather difficult”, and “Difficult” are coded as -1.5, -0.5, 0.5, and 1.5, respectively.

Figure C.3: Uncertainty (*diff_pred*) for combinations of business situation and expectations



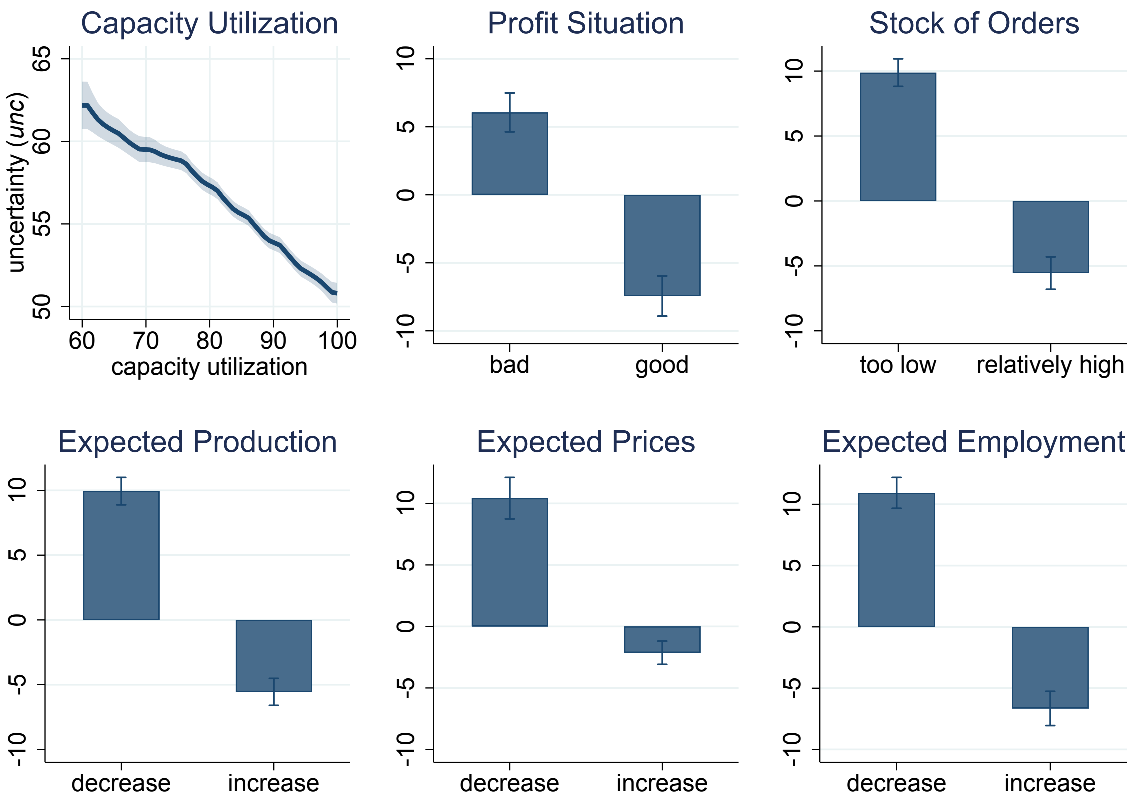
Notes: The bar chart illustrates the mean values of uncertainty (*diff_pred*) by the nine combinations of the categorical responses to the trichotomous questions about the business situation and business expectations described in Section 3.2.2. Each mean is based on at least 527 firm-time observations. For this illustration, the categories of *diff_pred* "Easy", "Rather Easy", "Rather difficult", and "Difficult" are coded as 0, 1, 2, and 3, respectively. The underlying sample from the spans from April 2019 to January 2020.

Table C.1: Uncertainty by interaction dummies of business situation and expectations

	(1) POLS	(2) FE
Situation good and expectations unchanged	6.677***	4.629***
	(0.774)	(0.409)
Situation good and expectations unfavorable	22.35***	14.49***
	(1.054)	(0.677)
Situation satisfactory and expectations favorable	10.01***	8.992***
	(0.899)	(0.544)
Situation satisfactory and expectations unchanged	13.21***	11.70***
	(0.834)	(0.506)
Situation satisfactory and expectations unfavorable	22.43***	16.89***
	(0.953)	(0.601)
Situation bad and expectations favorable	19.93***	17.63***
	(1.274)	(0.821)
Situation bad and expectations unchanged	20.57***	19.09***
	(1.325)	(0.740)
Situation bad and expectations unfavorable	26.31***	21.21***
	(1.223)	(0.834)
Constant	42.73***	45.06***
	(0.800)	(0.405)
No. of obs.	46248	46248
R-squared	0.14	0.55

Notes: Results from OLS and fixed effects regressions. The dependent variable is uncertainty (*unc*). The regressors are are based on the categorical questions on expectations and the business situation described in Section 3.2.2. In both regressions, the baseline category is a dummy for a good situation and favorable expectations. Standard errors in parentheses, clustered by firm; * p < 0.10, ** p < 0.05, *** p < 0.01.

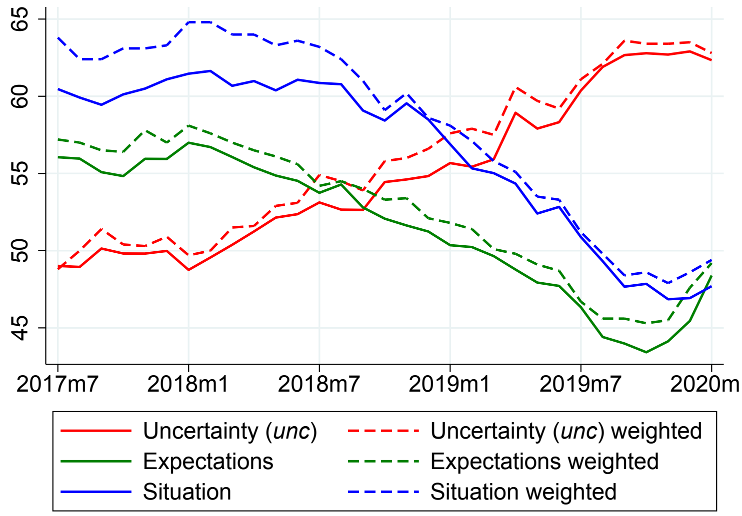
Figure C.4: Total variation of uncertainty by variables of business activity



Notes: The top left plot displays a non-parametric kernel regression line of degree zero with shaded 95% confidence bands for the relationship between uncertainty (*unc*) and capacity utilization in percent. I restrict the x-axis to the inter-decile range of capacity utilization for better visibility. The figure further presents bar charts illustrating coefficients from separate pooled OLS regressions of uncertainty (*unc*) on categorical variables from the ifo Business Survey, as denoted in the titles of the subplots. In particular, the regressors are dummies based on two categorical answers (labels at the x-axes). Thus, each bar corresponds to a coefficient relative to the middle category, which is "unchanged" in case of all variables except the stock of orders and the profit situation. For the latter two variables, the middle categories are labeled "sufficient" and "satisfactory", respectively. The whiskers at the bars are 95% confidence intervals. Capacity utilization is available once a quarter, the profit situation biannually, and all other variables in monthly frequency.

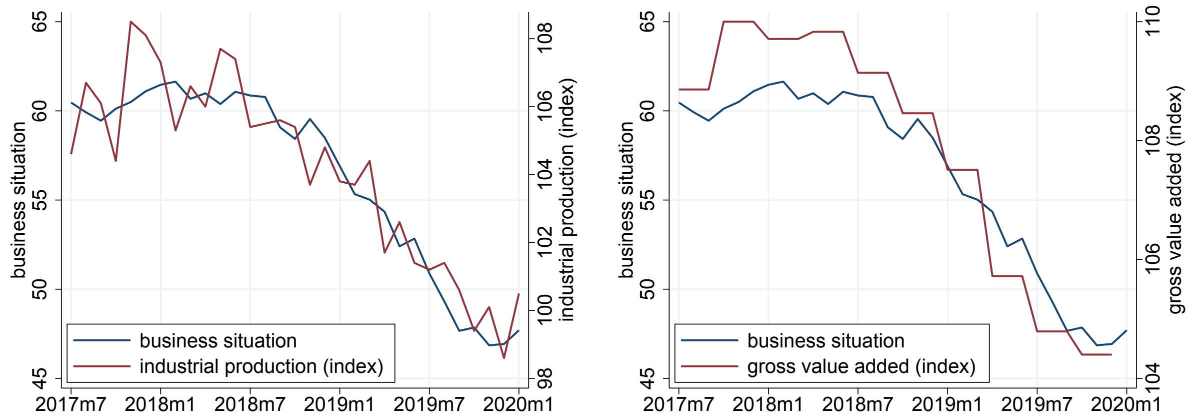
3.D Subjective Uncertainty in the Aggregate

Figure D.1: Weighted and unweighted time series



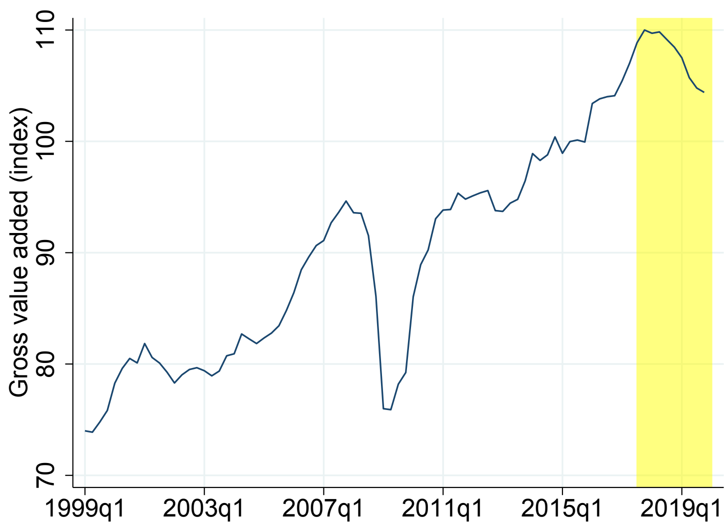
Notes: The figure presents weighted and unweighted aggregate time series of subjective uncertainty, business expectations and an assessment of the respondents' current business situation. These measures are based on the firm-level answers to questions 1, 2, and 3 in Section 3.2.2. The labels at the vertical axis are numbers from a visual analogue scale that ranges from 0 to 100. The weighted series are computed following the standard aggregation approach at ifo described in Sauer and Wohlrabe (2020). Weighting occurs in a two-step procedure: in the first step, observations are aggregated to the 2-digit WZ 08 sector level using firm size weights. In the second step, gross value added weights based on data from the German Statistical Office are used to aggregate from the 2-digit sector level to total manufacturing. The unweighted series are based on simple averages.

Figure D.2: Business situation vs. industrial production and gross value added



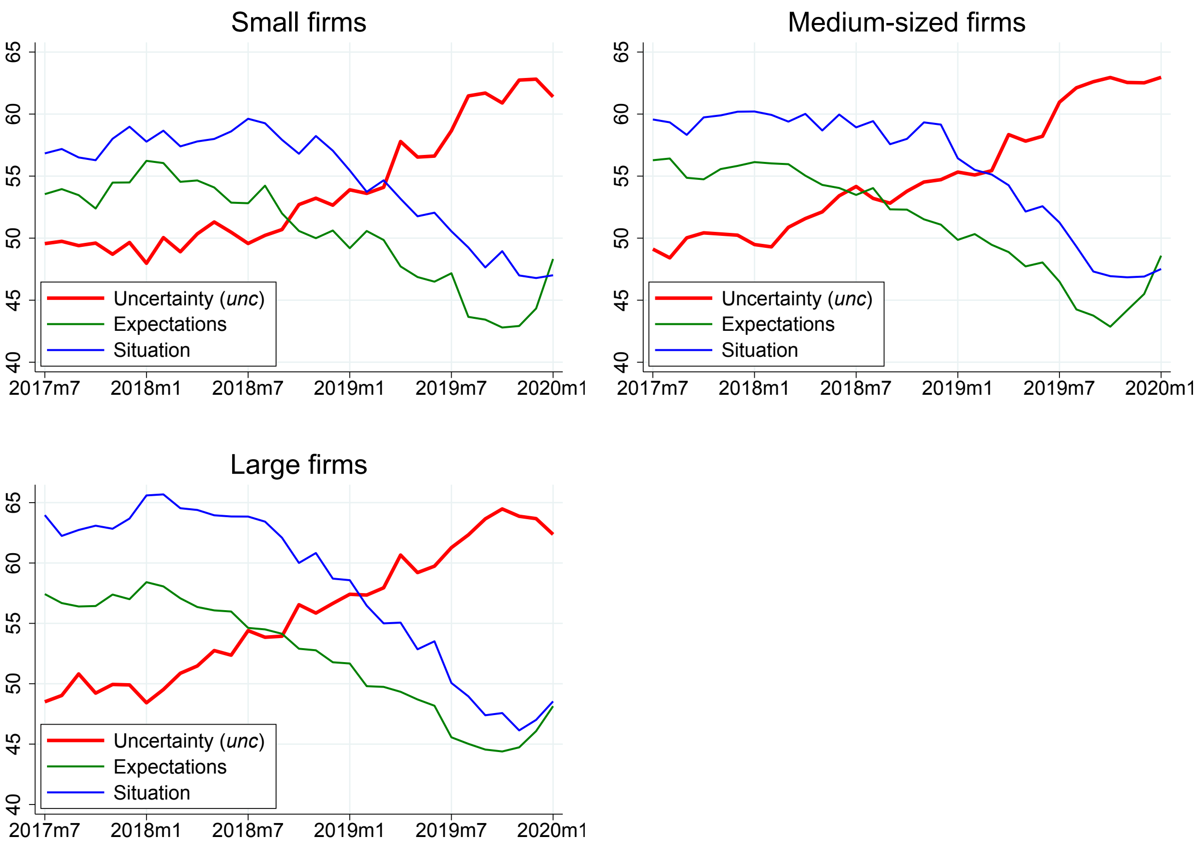
Notes: The left plot shows the unweighted average of the assessment of the business situation by manufacturing firms described in Section 3.2.2 and a monthly index of seasonally and calendar adjusted industrial production in the manufacturing sector from Eurostat. The right plot depicts the unweighted average of the business situation from manufacturing firms with a quarterly series of seasonally and calendar adjusted gross value added in constant prices for the manufacturing sector, provided by the German Federal Statistical Office.

Figure D.3: Long time series of gross value added in manufacturing



Notes: The figure depicts a quarterly index of seasonally and calender adjusted gross value added in manufacturing from Q1 1999 to Q4 2019. The sample period from Q3 2017 to Q4 2019 is marked in yellow. Note that the sample also includes January 2020. However, due to the impact of the COVID-19 crisis in March 2020, I leave out the value of the gross value added series for Q1 2020.

Figure D.4: Time series of uncertainty, expectations, and situation by firm size

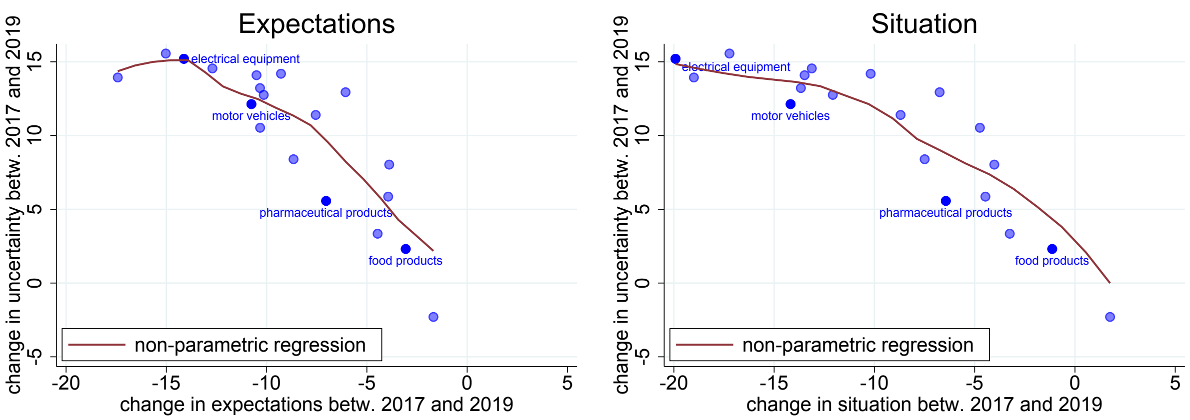


Notes: The figure presents time series of unweighted means of subjective uncertainty, business expectations and an assessment of the respondents' current business situation. These measures are based on the firm-level answers to questions 1, 2, and 3 in Section 3.2.2. I categorize firms in three size classes based on the number of employees, following the definition of the German Federal Statistical Office: small firms have less than 50 employees, medium-sized firms between 50 and 249 employees, and large firms 250 or more employees.

3.E Variation in Uncertainty and Sectoral Performance

Industries in the manufacturing sector are typically affected differently by an economic downturn. More cyclical sectors such as vehicle production or machinery tend to contract more than industries with rather stable demand, such as the food or pharmaceutical industries. The aim of this appendix is to better understand the drivers of the aggregate increase in perceived uncertainty. Does uncertainty increase fairly evenly in all sectors, or are different sectoral paths in the economic downturn related to sectoral heterogeneity in uncertainty?

Figure E.1: Changes in uncertainty, expectations, and the situation by sector



Notes: The left plot of the figure presents a scatter plot and a non-parametric kernel regression line of degree zero with an epanechnikov kernel and the "rule of thumb" bandwidth for the relationship between the change in average uncertainty (*unc*) and the change in average business expectations between 2017 and 2019 at the 2-digit WZ08 sector level. In particular, for each sector, I take averages of uncertainty and expectations over two periods, respectively: July through December in 2017 and July through December in 2019, before computing the time-differences between these averages. The right plot replicates the left plot, but replaces business expectations with the assessment of the business situation. For both plots, I exclude sectors 12, 15, 19, 30, and 33, for which I have less than 10 observations in at least one month of the two time periods. The assessments of the business situation, expectations, and uncertainty are based on questions 1, 2, and 3 in Section 3.2.2. Responses are elicited using visual analogue scales that range from 0 to 100, respectively.

To answer this question, I compare uncertainty (*unc*), expectations, and the business situation for a time period of low aggregate uncertainty in the beginning of the sample with a time period of high aggregate uncertainty in the end of the sample. For each 2-digit sector from the WZ08 classification, I compute averages of the three variables for the six months from July to December 2017, and from July to December 2019, respectively.[32] Taking differences of these averages allows me to compare changes in uncertainty to changes in expectations and changes in the business situation at the industry level. These comparisons are illustrated in Figure E.1.

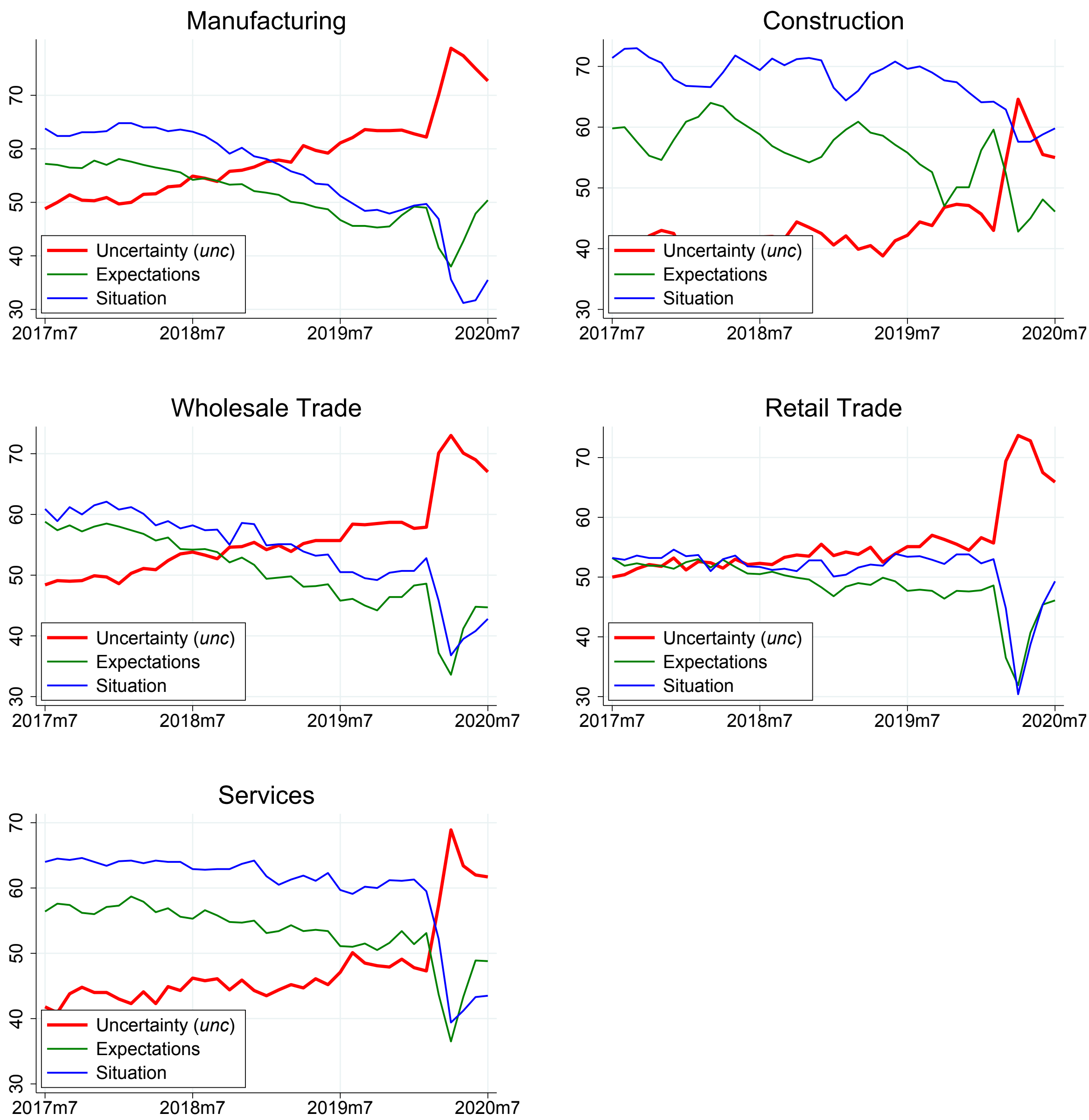
[32] The German WZ08 classification, short for "Klassifikation der Wirtschaftszweige 2008" is closely related to the European industry classification system NACE Rev. 2.

As expected, the two scatter plots show a sectoral heterogeneity in the change in expectations and the change in the assessment of the business situation between the second half of 2017 and the second half of 2019. This is the variation along the horizontal axes of the two plots, respectively. For instance, cyclical sectors, such as the industries producing motor vehicles and electrical equipment, underwent a large decline of their business situation by approximately 14 and 20 points on the visual analogue scale, respectively. The food and pharmaceutical sectors, on the other hand, reported a decline of only one and six points, respectively.

As the main result of this exercise, I find that uncertainty increased more in industries that experienced a larger decline in expectations and in the business situation. The negative correlations are high: the coefficient between changes in uncertainty and changes in expectations is -0.83; for changes in uncertainty vs. changes in the business situation the coefficient is -0.87. Thus, uncertainty did not rise evenly across all industries. Heterogeneity in sectoral performance is reflected in heterogeneity in uncertainty. This implies that the aggregate increase in uncertainty in the sample period was driven by industries whose situation and expectations deteriorated the most.

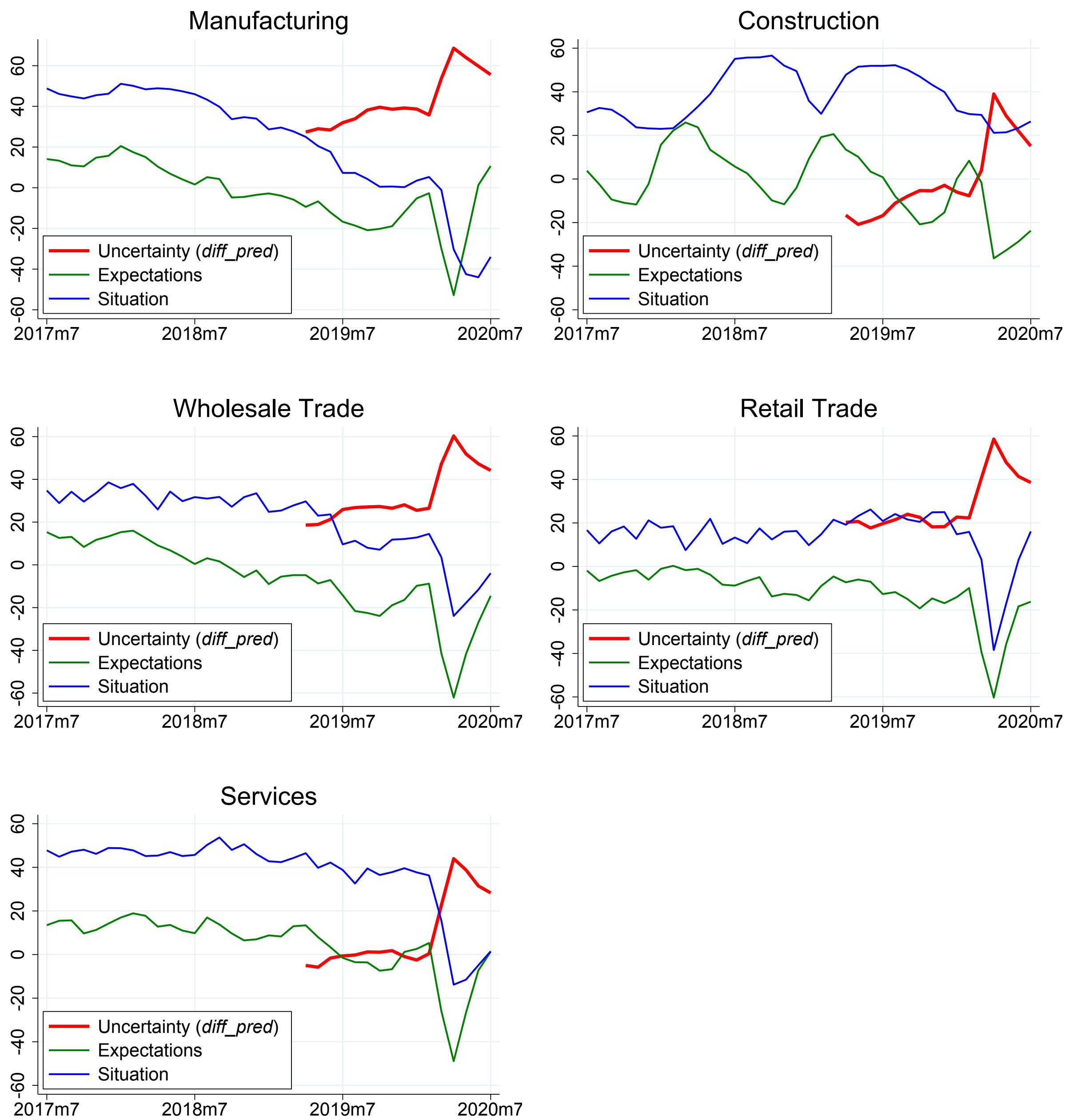
3.F Case Study: COVID-19 Crisis

Figure F.1: Uncertainty (*unc*), expectations, and business situation by major sector



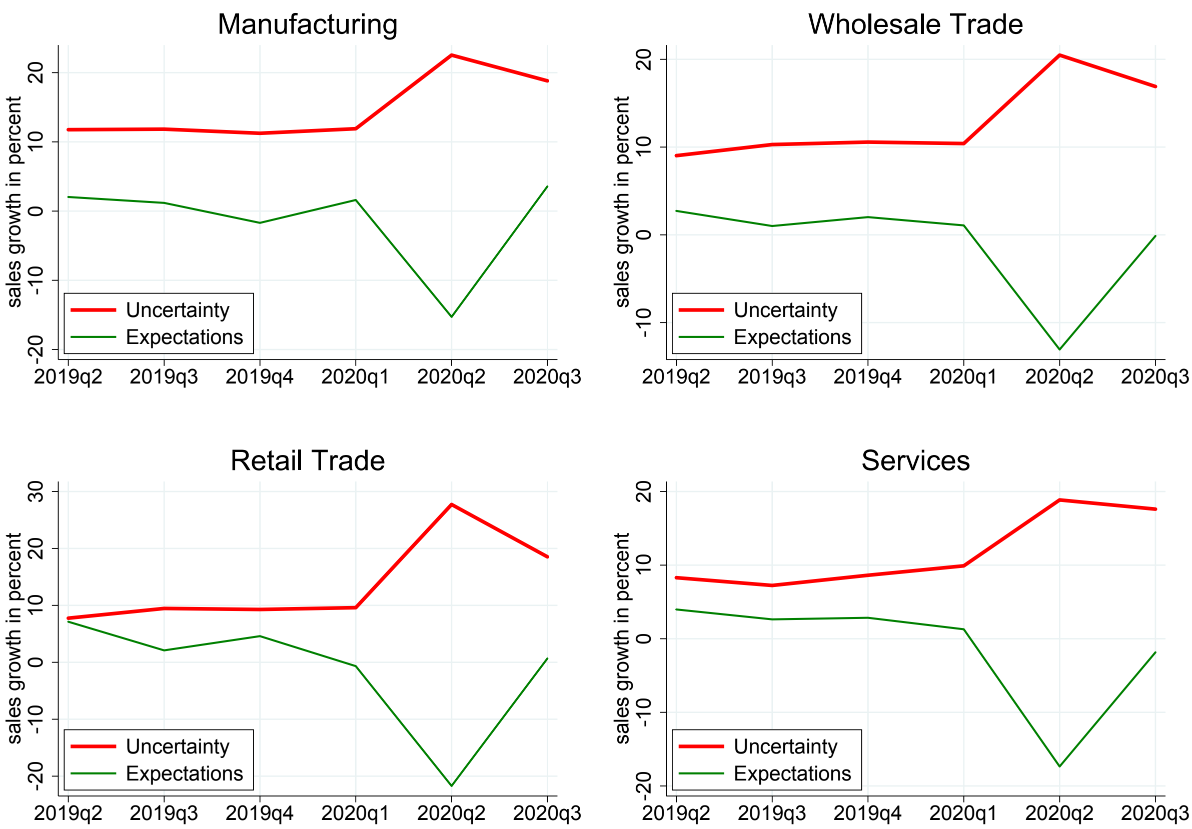
Notes: The figure presents size-weighted time series of subjective uncertainty (*unc*), expectations, and the business situation for five major sectors of the German economy. The survey responses are elicited using visual analogue scales as described in Section 3.2.2.

Figure F.2: Uncertainty (*diff_pred*), expectations, and business situation by major sector



Notes: The figure shows size-weighted time series of uncertainty (*diff_pred*) for five major sectors of the German economy. They are constructed as balance statistics using the responses to question 4 described in Section 3.2.2. The weights are -1 for the answer option "easy", -0.5 for "rather easy", 0.5 for "rather difficult", and 1 for "difficult". The other series are balance statistics from ifo's categorical questions on expectations and the business situation.

Figure F.3: Sales growth uncertainty, expectations, and business situation by major sector



Note: The figure shows size-weighted time series of quantitative expectations and uncertainty about quarter-over-quarter sales growth for four major sectors of the German economy. Uncertainty is computed as the difference between expectations in the best and in the worst case, as described in Bachmann et al. (2018). Its unit for uncertainty at the vertical axis is percentage points. The data stems from a survey supplement to the ifo Business Survey. It is available for all four major sectors since Q2 2019.

Below is the author's English translation of a special question in the ifo Business Survey from April 2020. For the baseline analysis in section 3.6.2, I use the responses on whether or not businesses reduced employment and whether or not they postponed investment projects. Additional regressions use the responses on short-time work and the cancellation of investment projects.

Which measures has your firm taken in response to the Corona pandemic?

Operations:

- □ Intensified use of working from home
- □ Short-time work
- □ Reduction of time accounts and leave days
- □ Reduction of employment (e.g., lay-offs, desist from extensions)
- □ Plant closure, stop of production
- □ Increased stock-keeping
- □ Change of suppliers / diversification of supply chains

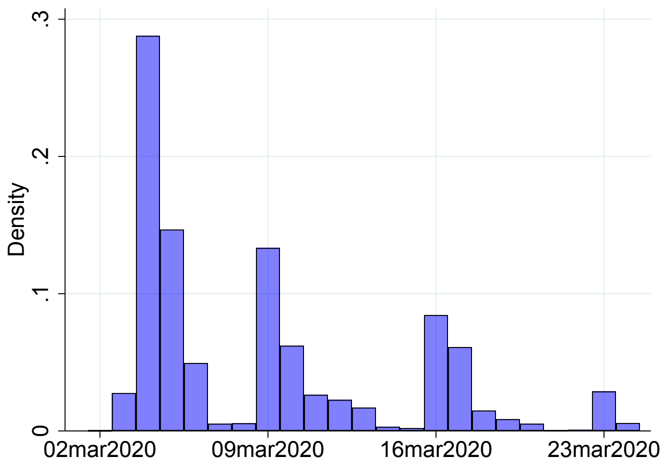
Finances / Investment:

- □ Use of existing credit lines
- □ Acquisition of new credit lines
- □ Application for public liquidity facilities
- □ Postponement of investment projects
- □ Cancellation of investment projects

Table F.1: Selected events in the onset of the COVID-19 crisis in Germany

Date	Event
March 2	The German Robert Koch Institute raises the threat level for the population to "moderate" because of COVID-19.
March 6	The German Health Minister rules out "any measure leading to restrictions on travel" within the European Union.
March 8	Recommendation of the German Health Minister to cancel events with more than 1000 participants.
March 9	Second death because of COVID-19 in Germany; more than 1,200 verified infections.
March 12	Federal and State governments recommend to avoid gatherings and social contacts.
March 13	Schools and childcare facilities close in almost all federal states.
March 16	German federal borders are closed; start of shutdown in which most shops and many public facilities are being closed.

Figure F.4: Histogram of the submission dates of the responses in March 2020



Note: Histogram of the submission dates of the questionnaires of the ifo Business Survey in March 2020. It was conducted from March 2 to March 24.

Table F.2: Representativeness of subsample of firms responding from March 16 to 24

	March 2 to 15		March 16 to 24	
	Mean	N	Mean	N
Firm characteristics				
Dummy small firms	0.557	4,767	0.546	1,269
Dummy medium firms	0.297	4,767	0.284	1,269
Dummy large firms	0.143	4,767	0.164	1,269
Dummy manufacturing	0.319	4,767	0.251	1,269
Dummy construction	0.093	4,767	0.128	1,269
Dummy wholesale & retail trade	0.245	4,767	0.199	1,269
Dummy services	0.342	4,767	0.422	1,269
Responses in February 2020				
Situation (visual analogue scale)	53.5	3,367	54.7	809
Expectations (visual analogue scale)	51.2	3,370	52.0	806
Uncertainty (*unc*) (visual analogue scale)	55.4	3,367	54.5	804
Dummy situation bad	0.157	4,251	0.136	920
Dummy situation good	0.335	4,251	0.370	920
Dummy expectation unfavorable	0.213	4,251	0.192	920
Dummy expectation favorable	0.178	4,251	0.184	920
Dummy uncertainty (*diff_pred*): easy or rather easy to predict	0.343	4,224	0.357	908
Dummy uncertainty (*diff_pred*): rather difficult to predict	0.532	4,224	0.537	908
Dummy uncertainty (*diff_pred*): difficult to predict	0.125	4,224	0.106	908
Responses in April 2020				
Dummy investment postponed	0.405	4,248	0.426	1,004
Dummy employment reduced	0.151	4,248	0.161	1,004
Dummy investment canceled	0.196	4,248	0.187	1,004
Dummy short-time work	0.471	4,248	0.488	1,004

Notes: The table presents means and the number of observations for a list of variables for two subsamples: firms the responded between March 2 and March 15, and firms that responded between March 16 and March 24. The top panel of the table presents the shares and frequencies of the responses from three size classes and four major economic sectors, respectively. The second panel considers past responses of the firms from February 2020 about the business situation, expectations, and uncertainty. The last panel shows the firms' subsequent responses in April 2020 about investment and employment decisions.

Table F.3: Correlation of regressors, levels and changes

	ΔUnc. in $t-1$	Unc. in $t-2$	ΔExp. in $t-1$	Exp. in $t-2$	ΔSit. in $t-1$	Sit. in $t-2$
ΔUnc. in $t-1$	1.00					
Unc. in $t-2$	-0.53	1.00				
ΔExp. in $t-1$	-0.21	0.05	1.00			
Exp. in $t-2$	0.18	-0.32	-0.46	1.00		
ΔSit. in $t-1$	-0.23	0.19	0.47	-0.24	1.00	
Sit. in $t-2$	0.31	-0.49	-0.20	0.53	-0.36	1.00

Notes: Pairwise correlations of main regressors in Table F.5: uncertainty (*unc*), expectations, and business situation as levels in February ($t-2$) and as month-over-month changes in March 2020 ($t-1$). These variables are based on the responses to questions 1, 2, and 3 in Section 3.2.2

Table F.4: Relationship between other corporate investment and employment decisions and past uncertainty, expectations, and situation

Dependent variable:	decision: cancellation of investment projects					decision: short-time work				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
ΔUncertainty in $t-1$	0.000500		-0.000694	-0.000678	-0.000323	0.000403		-0.0000603	-0.000119	0.000232
	(0.62)		(-0.86)	(-0.81)	(-0.37)	(0.60)		(-0.10)	(-0.20)	(0.35)
Uncertainty in $t-2$	0.00314***		0.00113	-0.0000990	0.000368	0.00303***		0.00142*	0.00102	0.00121
	(3.14)		(1.08)	(-0.09)	(0.35)	(3.90)		(1.96)	(1.33)	(1.36)
ΔExpectations in $t-1$		-0.00559***	-0.00571***	-0.00251**	-0.00207**		-0.00312***	-0.00288***	-0.00189**	-0.00194**
		(-6.31)	(-6.09)	(-2.57)	(-2.14)		(-4.14)	(-3.65)	(-2.31)	(-2.36)
Expectations in $t-2$		-0.00686***	-0.00616***	-0.00139	-0.000962		-0.00630***	-0.00557***	-0.00384***	-0.00481***
		(-5.54)	(-4.68)	(-0.97)	(-0.68)		(-6.37)	(-5.46)	(-3.39)	(-4.11)
ΔSituation in $t-1$				-0.00705***	-0.00659***				-0.00221***	-0.00318***
				(-8.13)	(-6.88)				(-2.87)	(-3.55)
Situation in $t-2$				-0.00820***	-0.00618***				-0.00259***	-0.00244**
				(-7.53)	(-5.19)				(-2.82)	(-2.31)
Dummy medium sized firms					0.0919**					0.00321
					(2.14)					(0.09)
Dummy large firms					0.116**					0.0670
					(2.08)					(1.41)
Sector dummies					YES					YES
No. of firms	660	667	656	653	602	660	667	656	653	586
Pseudo R-sq.	0.012	0.052	0.057	0.14	0.22	0.029	0.072	0.080	0.099	0.17

Notes: Average marginal effects from probit regressions. The dependent variable in columns 1 to 5 is a dummy for the decision to cancel investment projects because of the COVID-19 crisis, in columns 6 to 10 it is a dummy for the decision to implement short-time work because of the COVID-19 crisis. Information on firms' decisions stems from the ifo Business Survey in April 2020. The regressors are levels of uncertainty (*unc*), expectations, and business situation from February 2020, and month-over-month changes from March 2020. These measures are based on the responses to questions 1, 2, and 3 in Section 3.2.2. t-statistics in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table F.5: Robustness linear probability model: relationship corporate decisions and past uncertainty, expectations, and situation

Dependent variable:	decision: postponement of investment					decision: reduction of the number of employees				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
ΔUncertainty in $t-1$	0.00148*		0.000567	0.000682	0.000660	0.000156		-0.000399	-0.000237	0.000215
	(1.86)		(0.70)	(0.83)	(0.75)	(0.23)		(-0.59)	(-0.36)	(0.36)
Uncertainty in $t-2$	0.00551***		0.00457***	0.00452***	0.00394***	0.00210***		0.000564	0.000474	0.000719
	(5.85)		(4.61)	(4.28)	(3.41)	(2.60)		(0.68)	(0.56)	(0.90)
ΔExpectations in $t-1$		-0.00528***	-0.00464***	-0.00312***	-0.00317***		-0.00297***	-0.00289***	-0.00133*	-0.000779
		(-6.06)	(-5.01)	(-3.00)	(-2.91)		(-4.55)	(-4.17)	(-1.80)	(-1.05)
Expectations in $t-2$		-0.00437***	-0.00234*	-0.00127	-0.00105		-0.00572***	-0.00535***	-0.00408***	-0.00402***
		(-3.46)	(-1.77)	(-0.89)	(-0.70)		(-5.57)	(-4.83)	(-3.68)	(-3.58)
ΔSituation in $t-1$				-0.00327***	-0.00324***				-0.00324***	-0.00271***
				(-3.19)	(-2.84)				(-3.93)	(-3.27)
Situation in $t-2$				-0.00194*	-0.00141				-0.00222***	-0.00156*
				(-1.70)	(-1.08)				(-2.89)	(-1.93)
Dummy medium sized firms					0.0339					0.0302
					(0.74)					(0.85)
Dummy large firms					0.0289					0.0222
					(0.47)					(0.51)
Constant	0.0788	0.526***	0.169*	0.210*	-0.195	0.0337	0.385***	0.344***	0.390***	0.195*
	(1.25)	(8.58)	(1.75)	(1.87)	(-1.37)	(0.63)	(7.21)	(4.04)	(4.10)	(1.87)
Sector dummies					YES					YES
No. of firms	660	667	656	653	653	660	667	656	653	653
R-sq.	0.048	0.052	0.085	0.100	0.21	0.016	0.064	0.066	0.094	0.24

Notes: Results from OLS regressions. The dependent variable in columns 1 to 5 is a dummy for the decision to postpone investment projects because of the COVID-19 crisis, in columns 6 to 10 it is a dummy for the decision to reduce employment because of the COVID-19 crisis. Information on firms' decisions stems from the ifo Business Survey in April 2020. The regressors are levels of uncertainty (*unc*), expectations, and business situation from February 2020, and month-over-month changes from March 2020. These measures are based on the responses to questions 1, 2, and 3 in Section 3.2.2. Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table F.6: Robustness manufacturing excluded: relationship corporate decisions and past uncertainty, expectations, and situation

Dependent variable:	decision: postponement of investment					decision: reduction of the number of employees				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
ΔUncertainty in $t-1$	0.00213**		0.000985	0.00115	0.00142	0.000637		-0.000101	0.000104	0.000730
	(2.31)		(1.10)	(1.26)	(1.53)	(0.82)		(-0.15)	(0.16)	(1.09)
Uncertainty in $t-2$	0.00493***		0.00428***	0.00407***	0.00457***	0.00288***		0.00154*	0.00151*	0.00220**
	(4.37)		(3.51)	(3.25)	(3.58)	(3.12)		(1.71)	(1.71)	(2.29)
ΔExpectations in $t-1$		-0.00576***	-0.00525***	-0.00345***	-0.00304**		-0.00384***	-0.00364***	-0.00137	-0.000935
		(-5.70)	(-4.96)	(-2.89)	(-2.49)		(-3.96)	(-3.74)	(-1.51)	(-1.15)
Expectations in $t-2$		-0.00300**	-0.00116	0.000363	0.00101		-0.00508***	-0.00420***	-0.00199	-0.00229
		(-2.05)	(-0.74)	(0.21)	(0.57)		(-3.81)	(-3.08)	(-1.44)	(-1.62)
ΔSituation in $t-1$				-0.00336***	-0.00295**				-0.00376***	-0.00291***
				(-3.18)	(-2.56)				(-4.82)	(-3.92)
Situation in $t-2$				-0.00268*	-0.00197				-0.00297***	-0.00189*
				(-1.93)	(-1.31)				(-2.80)	(-1.78)
Dummy medium sized firms					0.00302					0.0127
					(0.06)					(0.34)
Dummy large firms					0.0506					0.0165
					(0.71)					(0.31)
Sector dummies					YES					YES
No. of firms.	487	492	484	481	464	487	492	484	481	424
Pseudo R-sq.	0.028	0.049	0.071	0.088	0.15	0.032	0.082	0.091	0.16	0.27

Notes: Average marginal effects from probit regressions that exclude firms from the manufacturing sector. The dependent variable in columns 1 to 5 is a dummy for the decision to postpone investment projects because of the COVID-19 crisis, in columns 6 to 10 it is a dummy for the decision to reduce employment because of the COVID-19 crisis. Information on firms' decisions stems from the ifo Business Survey in April 2020. The regressors are levels of uncertainty (*unc*), expectations, and business situation from February 2020, and month-over-month changes from March 2020. These measures are based on the responses to questions 1, 2, and 3 in section 3.2.2. t-statistics in parentheses; * p < 0.10, ** p < 0.05, *** p < 0.01.

Table F.7: Robustness measurement error: relationship corporate decisions and past uncertainty, expectations, and situation

Dependent variable:	decision: postponement of investment					decision: reduction of the number of employees				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
ΔUncertainty* in $t-1$	0.000358		-0.00137	-0.00182	-0.00202	0.00121		0.000334	-0.0000395	-0.000562
	(0.18)		(-0.65)	(-0.87)	(-0.98)	(0.74)		(0.21)	(-0.03)	(-0.39)
Uncertainty* in $t-2$	0.00469***		0.00316*	0.000726	-0.000465	0.00336***		0.00133	-0.000279	-0.00150
	(2.95)		(1.84)	(0.39)	(-0.25)	(2.62)		(0.99)	(-0.20)	(-1.03)
ΔExpectations* in $t-1$		-0.0108***	-0.0106***	-0.00872***	-0.00857***		-0.00928***	-0.00875***	-0.00575**	-0.00522*
		(-4.53)	(-4.38)	(-3.52)	(-3.48)		(-3.31)	(-3.13)	(-2.20)	(-1.86)
Expectations* in $t-2$		-0.00906***	-0.00751***	-0.00512**	-0.00511**		-0.00948***	-0.00867***	-0.00607***	-0.00622***
		(-4.53)	(-3.57)	(-2.38)	(-2.42)		(-4.42)	(-3.99)	(-3.07)	(-2.92)
ΔSituation* in $t-1$				-0.00609***	-0.00666***				-0.00607***	-0.00691***
				(-3.71)	(-3.84)				(-4.86)	(-5.11)
Situation* in $t-2$				-0.00526***	-0.00488***				-0.00419***	-0.00460***
				(-4.14)	(-3.44)				(-4.50)	(-3.87)
Dummy medium sized firms					0.0249					0.0335
					(0.55)					(0.95)
Dummy large firms					0.0202					-0.0107
					(0.33)					(-0.23)
Sector dummies					YES					YES
No. of firms	654	650	639	629	606	654	650	639	629	542
Pseudo R-sq.	0.013	0.029	0.038	0.062	0.13	0.017	0.064	0.064	0.12	0.25

Notes: Average marginal effects from probit regressions. The dependent variable in columns 1 to 5 is a dummy for the decision to postpone investment projects, in columns 6 to 10 it is a dummy for the decision to reduce employment. Information on firms' decisions stems from the ifo Business Survey in April 2020. The right hand side variables marked with a star contain predicted values from regressions of the levels of uncertainty (*unc*), expectations, and business situation elicited using visual analogue scales in February 2020 on their categorical counter-parts, respectively. The other regressors marked with a star are predicted values from regressions of monthly changes in the visual analogue scale variables on changes in the categorical variables in March 2020. In case of uncertainty (*unc*), the predicted values stem from regressions on *diff_pred*. This implements the Obviously Related Instrumental Variable approach to account for independent and identically distributed measurement error. The regressors are based on the responses to questions 1, 2, 3, and 4 as well the categorical questions on business expectations and the situation presented in Section 3.2.2. t-statistics in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table F.8: Robustness uncertainty *diff_pred*: Relationship corporate decisions and past uncertainty, expectations, and situation

Dependent variable:	decision: postponement of investment					decision: reduction of the number of employees				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Uncertainty: negative change in $t-1$	0.101		0.0741	0.0857	0.0881	0.0294		0.0153	0.00843	0.0298
	(1.30)		(0.96)	(1.11)	(1.18)	(0.54)		(0.28)	(0.16)	(0.54)
Uncertainty: positive change in $t-1$	0.0974**		0.0381	0.0254	0.0193	0.0664**		0.0334	0.0180	-0.00291
	(2.51)		(0.92)	(0.61)	(0.45)	(2.26)		(1.08)	(0.60)	(-0.09)
Uncertainty: dummy 'rather difficult' in $t-2$	0.0958**		0.0620	-0.00130	-0.0344	0.0485*		0.0105	-0.0246	-0.0353
	(2.55)		(1.56)	(-0.03)	(-0.77)	(1.73)		(0.35)	(-0.78)	(-1.03)
Uncertainty: dummy 'difficult' in $t-2$	0.267***		0.163**	0.0727	0.0251	0.192***		0.102**	0.0551	-0.000124
	(4.04)		(2.30)	(0.96)	(0.33)	(4.20)		(2.02)	(1.09)	(-0.00)
Expectations: negative change in $t-1$		0.221***	0.194***	0.170***	0.155***		0.170***	0.156***	0.114***	0.0959**
		(5.18)	(4.26)	(3.63)	(3.24)		(4.17)	(3.70)	(2.75)	(1.98)
Expectations: positive change in $t-1$		-0.111	-0.106	-0.0853	-0.0649		-0.0670	-0.0625	-0.0323	-0.0383
		(-1.07)	(-1.02)	(-0.85)	(-0.65)		(-0.82)	(-0.79)	(-0.43)	(-0.55)
Expectations: dummy 'favorable' in $t-2$		0.00652	0.0217	0.0245	0.0279		-0.0218	-0.0185	-0.0151	-0.00840
		(0.16)	(0.51)	(0.57)	(0.64)		(-0.71)	(-0.58)	(-0.48)	(-0.24)
Expectations: dummy 'unfavorable' in $t-2$		0.314***	0.262***	0.183***	0.203***		0.265***	0.240***	0.175***	0.167***
		(5.75)	(4.49)	(2.95)	(3.24)		(5.71)	(4.87)	(3.70)	(3.22)
Situation: negative change in $t-1$				0.117***	0.139***				0.130***	0.139***
				(2.98)	(3.38)				(4.70)	(4.53)
Situation: positive change in $t-1$				-0.0389	-0.0628				-0.0594	-0.0836
				(-0.60)	(-0.99)				(-1.23)	(-1.63)
Situation: dummy 'good' in $t-2$				-0.137***	-0.144***				-0.0696**	-0.0544
				(-3.31)	(-3.29)				(-2.30)	(-1.57)
Situation: dummy 'bad' in $t-2$				0.104*	0.0865				0.112***	0.129***
				(1.81)	(1.47)				(3.05)	(3.12)
Dummy medium sized firms					0.0437					0.0483
					(1.07)					(1.56)
Dummy large firms					0.0558					0.0276
					(1.01)					(0.67)
Sector dummies					YES					YES
No. of firms	796	782	782	775	750	796	782	782	775	670
Pseudo R-sq.	0.019	0.036	0.043	0.060	0.11	0.029	0.065	0.073	0.12	0.24

Notes: Average marginal effects from probit regressions. The dependent variable in columns 1 to 5 is a dummy for the decision to postpone investment projects because of the COVID-19 crisis, in columns 6 to 10 it is a dummy for the decision to reduce employment because of the COVID-19 crisis. Information on firms' decisions stems from the ifo Business Survey in April 2020. The regressors are levels of uncertainty (*diff_pred)*, expectations, and business situation from February 2020, and month-over-month changes from March 2020. These measures are based on the responses to question 4 and the categorical questions on business expectations and the situation presented in Section 3.2.2. t-statistics in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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