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

Rüdiger Bachmann
Notre Dame, CEPR, CESifo, ifo

Kai Carstensen
University of Kiel, CESifo, ifo

Stefan Lautenbacher
ifo, LMU Munich

Martin Schneider
Stanford, CEPR, NBER

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Abstract

This paper 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 between Knightian and Bayesian responses 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.

Keywords: subjective beliefs, Knightian uncertainty, firms, measurement, survey data

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*E-mail: rbachman@nd.edu; carstensen@stat-econ.uni-kiel.de; lautenbacher@ifo.de; schneidr@stanford.edu.
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1 Introduction

There has been a lot of recent progress in measuring subjective beliefs of decision makers in firms. While traditional approaches ask qualitative questions that have categorical answers, 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 Tendency 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. 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 house-

[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).

holds. 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. (2018) 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. (2019) 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 re 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 introduces our data and provides a first set of summary statistics about Knightian responses. Section 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 4 studies the aggregate and idiosyncratic movements in Knightian responses.

2 Data

Our data come from an "uncertainty module" for manufacturing firms in the ifo Business Tendency Survey, designed in 2012 and first described in Bachmann et al. (2019). 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, now part of 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.

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., 2019) 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).[2] Finally, questions in the main survey that ask about realized outcomes (such as production) explicitly ask firms to ignore seasonal fluctuations. Consistent

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

with this, we observe only negligible seasonal effects in our data.

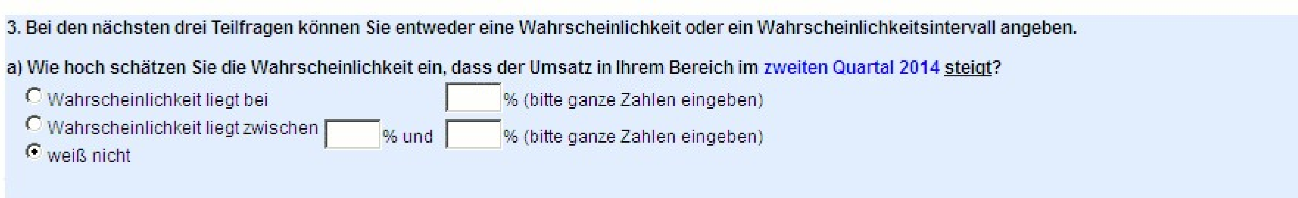
2.1 The subjective likelihood of a sales increase

Figure 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. The default option is to skip the question by checking "don't know" ("weiss nicht" in German), the third option checked in the screenshot. Once a respondent enters a number, the "don't know"-option becomes unchecked. The final box underneath part (c) allows firms to provide free-form text comments ("Anmerkungen").


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

Figure 1: Original survey questionnaire in German

Note: Original questionnaire from ifo's online module on subjective uncertainty in German; snapshot 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 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 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 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.

Table 1: Transition matrix for Knightian and Bayesian responses in two subsequent quarters

	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.

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; 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 provides summary statistics of probabilities submitted by firms. The distribution of probabilities in Bayesian responses is not too far away from uniform, with a mean of .45. 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.

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

Table 2: Summary statistics for Bayesian and Knightian probabilities

		Mean	SE(Mean)	P10	P25	P50	P75	P90
Bayesian	probability	0.45	0.01	0.00	0.10	0.50	0.80	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: Probabilities of Bayesian responses include certain observations, i.e., probabilities of 0 or 1. 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.

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.

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.

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 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.

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.[3] Again, distinguishing between different

[3]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.

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. 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.

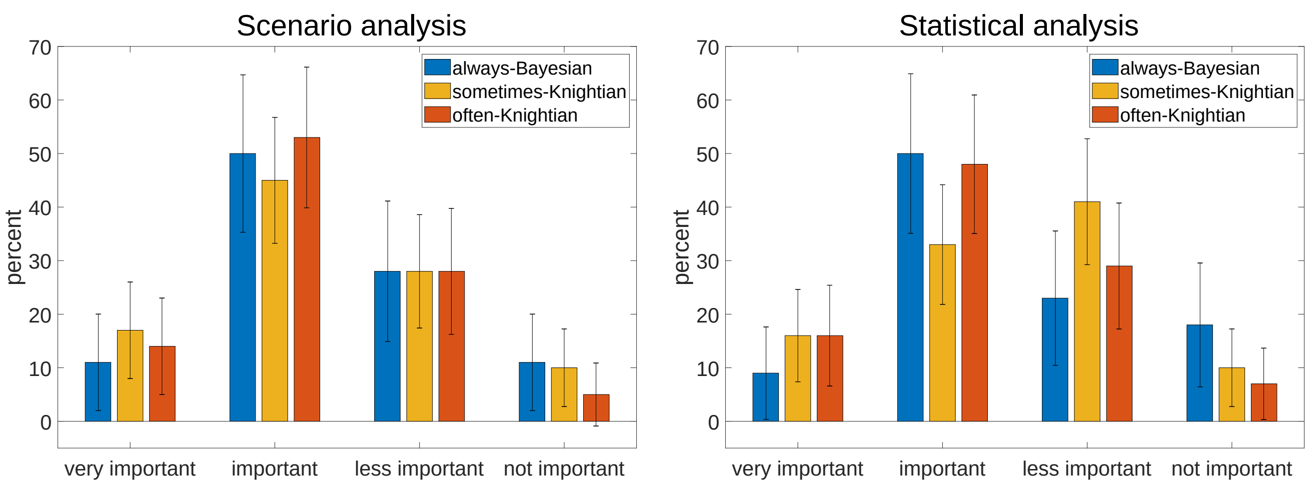


Figure 2: Importance of scenario analysis and statistical analysis

Note: 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.

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:

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.

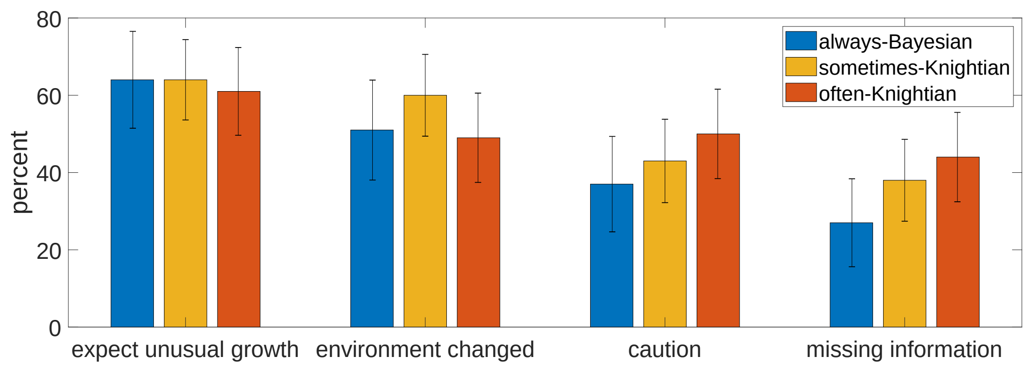


Figure 3: Motivation for stating a probability interval

Note: 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. Gray whiskers indicate ± 1.96 standard error bands.

Fig. 3 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 probability 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 significantly 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.

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. (2019). 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. (2019) 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.

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

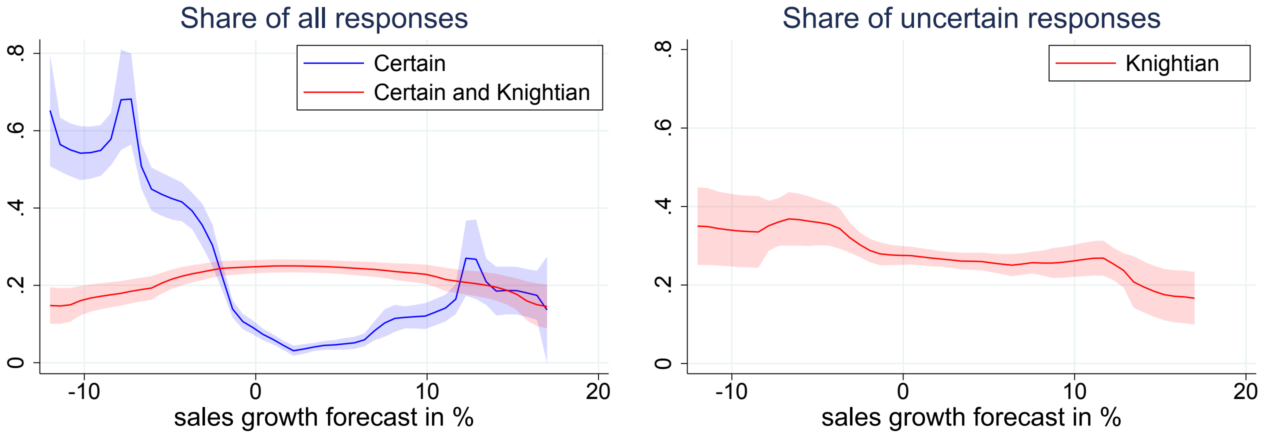


Figure 4: Response shares

Note: 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 certain plus Knightian responses (red), bandwidths are $h = .92$ and $h = 2.67$, respectively; in right panel: Knightian responses as a share of uncertain responses, bandwidth is $h = 1.52$.

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 4 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.[4] 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 4 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 5 relates the Knightian share to best and worst case scenarios contemplated by the

[4] 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.

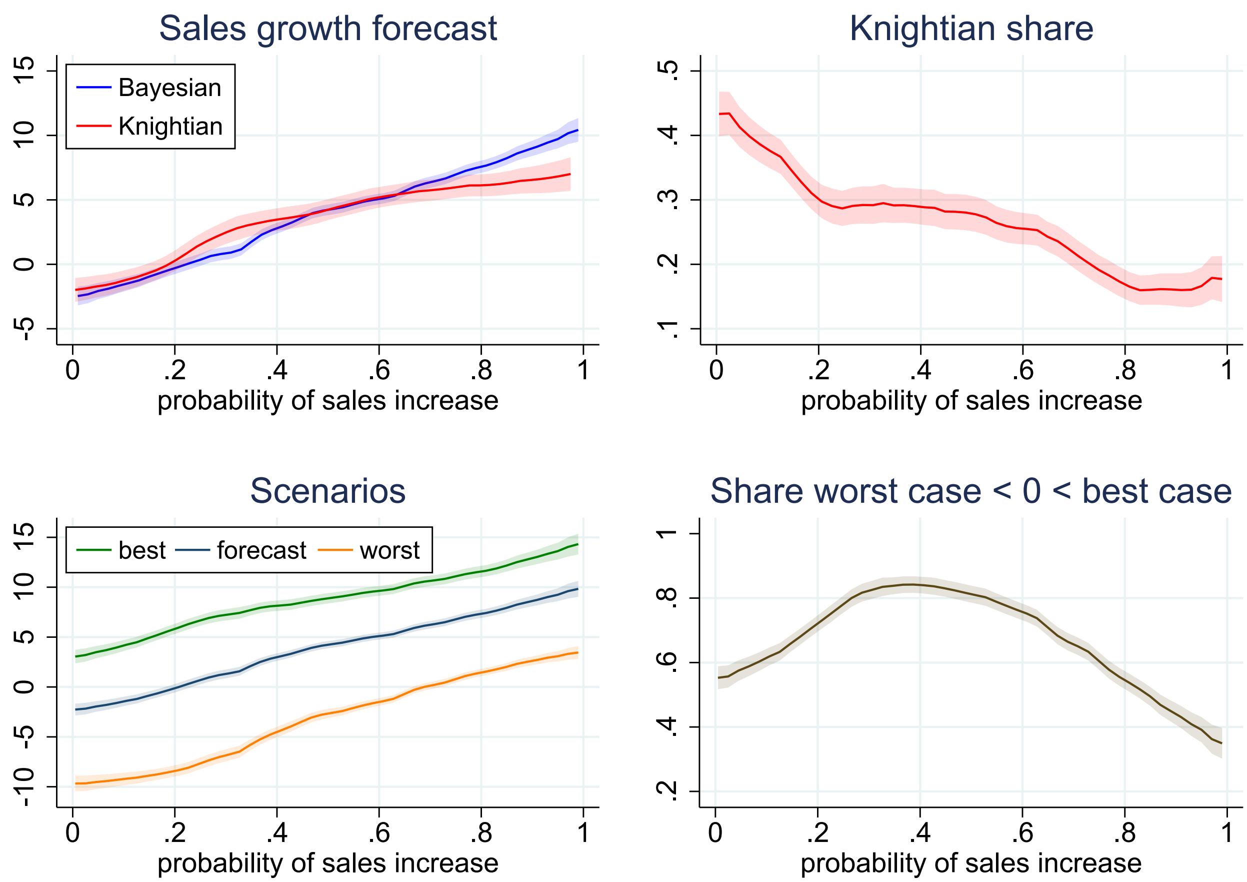


Figure 5: Predicted probabilities of a sales increase, forecasts, and scenarios

Note: 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.

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.

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.

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 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 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 5 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.

3.3 Calibration

Our results on firms' self assessment in Section 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 6. 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 6, 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.

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

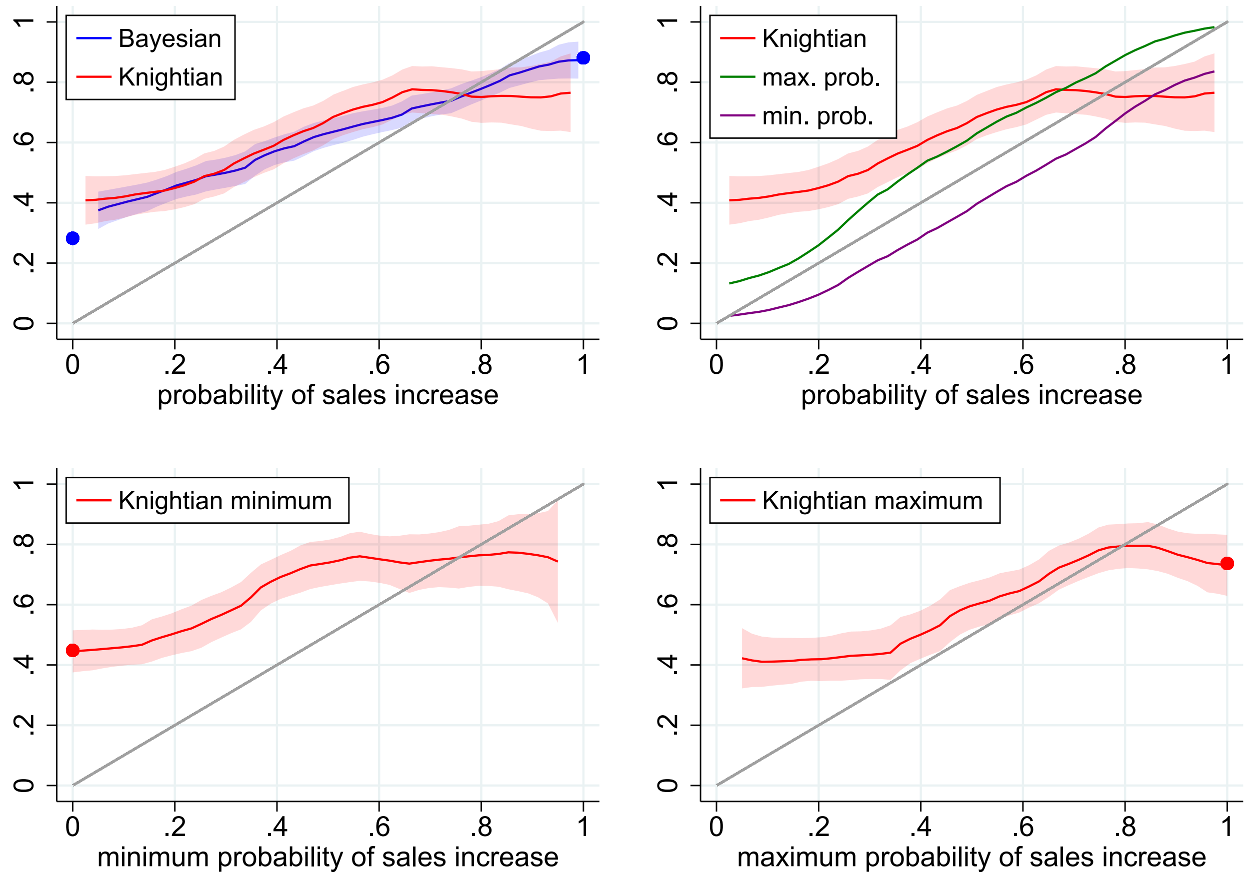


Figure 6: Calibration plot

Note: 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 $h = 0.078$. 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.

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 6 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 6 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 6 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.

4 Dynamics of Knightian responses

In this section, we study the evolution of Knightian responses over time. Figure 7 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 4.1 explores whether firm characteristics can predict the frequency of such switches.

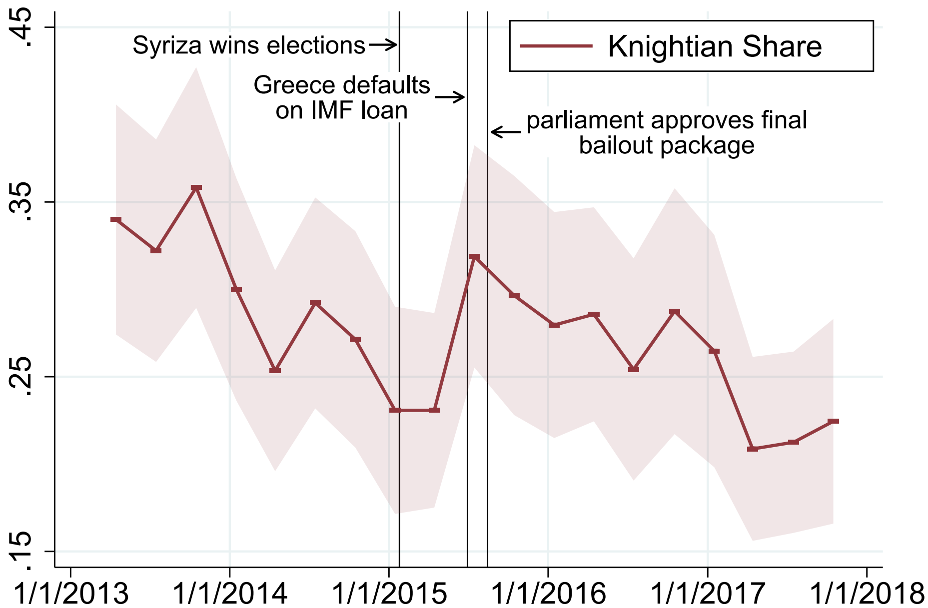


Figure 7: Time-variation of Knightian share

Note: 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 7 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. 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 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.

4.1 The persistence of Knightian spells in the cross section

Table 3 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 a *large* group with more than 250 workers as well as a *small* group 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 entire 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.

Table 3: 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.

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 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.

4.2 Knightian responses and macroeconomic risk

We now return to the time series evolution of the Knightian share in Figure 7. To further understand this evolution, Figure 8 plots Knightian shares for different groups of firms, and also overlays it with various 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.

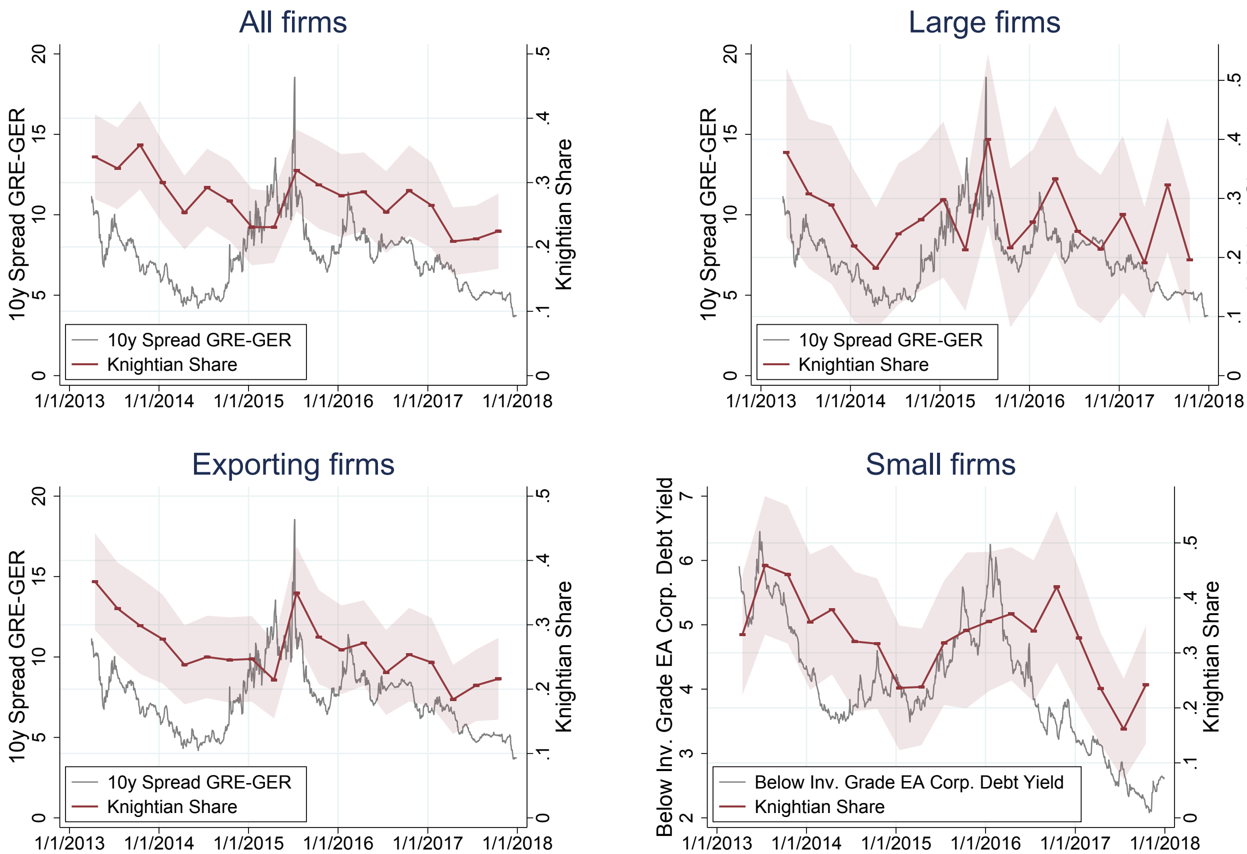


Figure 8: Time-variation of Knightian share with financial measures of macroeconomic risk

Note: 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).

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 AppendixB for details.

The estimated switching probabilities are displayed in Figure 9. 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 7. 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 8. 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.

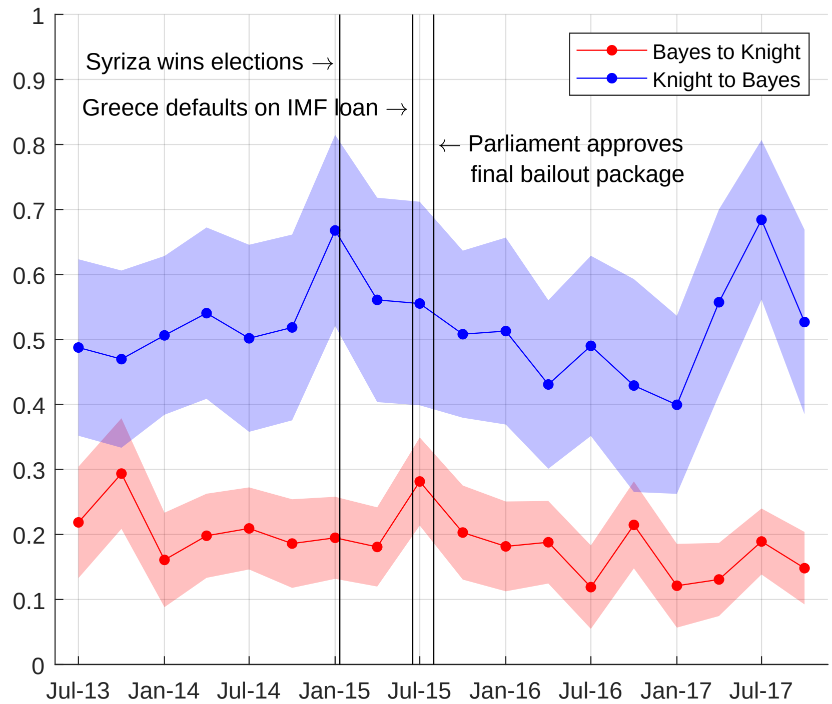


Figure 9: Time varying transition probabilities

Note: 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.

References

Altig, D., Barrero, J.M., Bloom, N., Davis, S.J., Meyer, B.H., Parker, N., 2019. Surveying Business Uncertainty. Working Paper 25956. National Bureau of Economic Research. URL: `http://www.nber.org/papers/w25956`, doi:`10.3386/w25956`.

Armantier, O., Bruine de Bruin, W., Topa, G., van der Klaauw, W., Zafar, B., 2015. Inflation expectations and behavior: Do survey respondents act on their beliefs? International Economic Review 56, 505–536.

Asparouhova, E., Bossaerts, P., Eguia, J., Zame, W., 2015. Asset pricing and asymmetric reasoning. Journal of Political Economy 123, 66–122. URL: `http://www.jstor.org/stable/10.1086/679283`.

Bachmann, R., Carstensen, K., Lautenbacher, S., Schneider, M., 2019. Uncertainty and Change:

Survey Evidence of Firms' Subjective Beliefs. Technical Report. mimeo, University of Notre Dame. URL: https://www3.nd.edu/~rbachman/BCLS_current.pdf.

Ben-David, I., Graham, J.R., Harvey, C.R., 2013. Managerial miscalibration. The Quarterly Journal of Economics 128, 1547–1584.

Bianchi, F., Ilut, C.L., Schneider, M., 2017. Uncertainty Shocks, Asset Supply and Pricing over the Business Cycle. The Review of Economic Studies 85, 810–854. URL: https://doi.org/10.1093/restud/rdx035, doi:10.1093/restud/rdx035, arXiv:https://academic.oup.com/restud/article-pdf/85/2/810/24473349/rdx035.pdf.

Bloom, N., Davis, S.J., Foster, L., Lucking, B., Ohlmacher, S., Saporta-Eksten, I., 2017. Business-Level Expectations and Uncertainty. mimeo, Stanford University.

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

Caballero, R., Simsek, A., 2013. Fire sales in a model of complexity. Journal of Finance 68, 2549–2587. URL: https://EconPapers.repec.org/RePEc:bla:jfinan:v:68:y:2013:i:6:p:2549-2587.

Coibion, O., Gorodnichenko, Y., Kumar, S., 2018. How do firms form their expectations? new survey evidence. American Economic Review 108, 2671–2713. URL: http://www.aeaweb.org/articles?id=10.1257/aer.20151299, doi:10.1257/aer.20151299.

Delavande, A., Ganguli, J., Mengel, F., 2019. Measuring Uncertainty Attitudes and their Impact on Behaviour in General Social Surveys. Technical Report. mimeo, University of Essex.

Dimmock, S., Kouwenberg, R., Mitchell, O., Peijnenburg, K., 2016. Ambiguity aversion and household portfolio choice puzzles: Empirical evidence. Journal of Financial Economics 119, 559–577. URL: https://EconPapers.repec.org/RePEc:eee:jfinec:v:119:y:2016:i:3:p:559-577.

Dominitz, J., Manski, C.F., 1997. Using expectations data to study subjective income expectations. Journal of the American Statistical Association 92, 855–867.

Dominitz, J., Manski, C.F., 2004. How should we measure consumer confidence? Journal of Economic Perspectives 18, 51–66.

Ellsberg, D., 1961. Risk, ambiguity, and the savage axioms. The Quarterly Journal of Economics 75, 643–669. URL: https://EconPapers.repec.org/RePEc:oup:qjecon:v:75:y:1961:i:4:p:643-669.

Epstein, L.G., Wang, T., 1994. Intertemporal asset pricing under knightian uncertainty. Econometrica 62, 283–322. URL: http://www.jstor.org/stable/2951614.

Gennaioli, N., Ma, Y., Shleifer, A., 2016. Expectations and investment. NBER Macroeconomics Annual 30, 379–442.

Gilboa, I., Schmeidler, D., 1989. Maxmin expected utility with non-unique prior. Journal of Mathematical Economics .

Giustinelli, P., Manski, C., Molinari, F., 2019. Precise or Imprecise Probabilities? Evidence from Survey Response on Late-onset Dementia. NBER Working Papers 26125. National Bureau of Economic Research, Inc. URL: https://EconPapers.repec.org/RePEc:nbr:nberwo:26125.

Giustinelli, P., Pavoni, N., 2017. The evolution of awareness and belief ambiguity in the process of high school track choice. Review of Economic Dynamics 25, 93–120. URL: https://EconPapers.repec.org/RePEc:red:issued:16-101.

Guiso, L., Jappelli, T., Pistaferri, L., 2002. An empirical analysis of earnings and employment risk. Journal of Business & Economic Statistics 20, 241–253.

Guiso, L., Jappelli, T., Terlizzese, D., 1992. Earnings uncertainty and precautionary saving. Journal of Monetary Economics 30, 307–337.

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

Hurd, M.D., McGarry, K., 2002. The predictive validity of subjective probabilities of survival. The Economic Journal 112, 966–985.

Ilut, C., Schneider, M., 2014. Ambiguous business cycles. American Economic Review 104, 2368–99. URL: https://EconPapers.repec.org/RePEc:aea:aecrev:v:104:y:2014:i:8:p:2368-99.

Juster, F.T., 1966. Consumer buying intentions and purchase probability: An experiment in survey design. Journal of the American Statistical Association 61, 658–696.

Juster, F.T., Suzman, R., 1995. An overview of the health and retirement study. The Journal of Human Resources 30, S7–S56.

Manski, C., Molinari, F., 2010. Rounding probabilistic expectations in surveys. Journal of Business & Economic Statistics 28, 219–231. URL: https://EconPapers.repec.org/RePEc:bes:jnlbes:v:28:i:2:y:2010:p:219-231.

Mietzner, D., 2009. Strategische Vorausschau und Szenarioanalysen. Hamburg: Springer Verlag.

Appendix A Questionnaire for fall 2018 meta-survey

Meta-Umfrage zur Zusatzumfrage "Unsicherheit"

ifo INSTITUT

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

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

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

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:

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:

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: [ ]

Appendix 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.,

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

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

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

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..