Surveying Business Uncertainty

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Abstract: We elicit subjective probability distributions from business executives about their own-firm outcomes at a one-year look-ahead horizon. In terms of question design, our key innovation is to let survey respondents freely select support points and probabilities in five-point distributions over future sales growth, employment, and investment. In terms of data collection, we develop and field a new monthly panel Survey of Business Uncertainty. The SBU began in 2014 and now covers about 1,750 firms drawn from all 50 states, every major nonfarm industry, and a range of firm sizes. We find three key results. First, firm-level growth expectations are highly predictive of realized growth rates. Second, firm-level subjective uncertainty predicts the magnitudes of future forecast errors and future forecast revisions. Third, subjective uncertainty rises with the firm's absolute growth rate in the previous year and with the magnitude of recent revisions to its expected growth rate. We aggregate over firm-level forecast distributions to construct monthly indices of business expectations (first moment) and uncertainty (second moment) for the U.S. private sector.

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Introduction

Uncertainty is a fundamental fact of economic life. Businesses and households grapple with uncertainty in forming plans and making decisions. The extent and nature of uncertainties change over time, sometimes gradually and sometimes abruptly, altering the outlook for decision makers and affecting their choices. Recent history offers some vivid examples: the 9/11 terrorist attacks, the Global Financial Crisis, banking and sovereign debt crises in the Eurozone, the June 2016 Brexit referendum, a dramatic escalation of trade policy tensions under the Trump Administration, and the coronavirus pandemic of 2020. These examples underscore the need for sound, flexible measures of uncertainty, so that we can better understand and model the relationship of perceived uncertainty to economic decisions, outcomes, and performance.

We would like to track the uncertainty that agents perceive in their external environments and the uncertainty they perceive about own future outcomes, e.g., a firm's future sales. A standard approach maintains rational expectations and some form of stationarity, so that past conditional volatility can serve as the basis for inferences about uncertainty over future outcomes. Examples include Bloom (2009), Fernández-Villaverde et al. (2011), Jurado, Ludvigson, and Ng (2015), and Colacito et al. (2018). Another approach treats the dispersion in point forecasts as a proxy for uncertainty (e.g., Bachmann, Elstner and Sims, 2013). Scotti (2016) uses surprises in economic data releases to proxy for uncertainty. Yet another approach relies on newspapers and other text sources to construct uncertainty measures, as in Baker, Bloom, and Davis (2016), Handley and Li (2018) and Hassan et al. (2019). Datta et al. (2017) offer an extensive overview of various approaches, with a focus on measuring uncertainty in the external environment.

While valuable, these approaches may not adequately capture the subjective uncertainty that agents perceive, which presumably is what drives their decisions. There is a now-large body of evidence that subjective expectations deviate systematically from the expectations implied by rational expectations with full use of available information.[1] In addition, many of the most prominent empirical proxies for uncertainty pertain to distinct theoretical concepts and differ in their statistical properties (Kozeniauskas et al., 2018). These observations argue for a measurement approach that gets directly at the uncertainty agents perceive without invoking assumptions about rationality, information, and stationarity.

We – a group of researchers at the Atlanta Fed, Chicago Booth and Stanford – set out in 2013 to develop and field a new survey instrument to measure the perceived uncertainty of senior decision makers in U.S. firms. In doing so, we built on earlier work that elicits subjective beliefs from households, as in Dominitz and Manski (1997) and Manski (2004).[2] We spent about a year on initial field testing of various question designs, conducting cognitive interviews, and creating the Survey of Business Uncertainty (SBU). Since 2014, the SBU has collected subjective probability distributions over own-firm future outcomes from a panel of business executives. We send them surveys each month and recruit new firms over time, with the aim of collecting long response histories for many firms. As of October 2019, we have data for 1,743 firms drawn from all 50 states, every major nonfarm industry, and a wide range of firm sizes.

[1] Examples include Coibion and Gorodnichenko (2012, 2015) and Bordalo et al. (2019) for professional forecasters, Malmendier and Tate (2005), Ben-David, Graham, and Harvey (2013), Gennaioli, Ma and Shleifer (2016) and Barrero (2020) for firm managers, Barber and Odean (2001), Bailey et al. (2011), Puetz and Ruenzi (2011) and Akepanidtaworn et al. (2019) for investors and mutual fund managers, and Roszypal and Schlaffmann (2017) for consumers.

[2] Manski (2004) is an early advocate of measuring subjective expectations by asking survey respondents to assign probabilities to pre-specified outcomes. Most of this work surveys households and consumers. The University of Michigan Survey of Consumers (www.sca.isr.umich.edu) has long asked households to assign probabilities to binary outcomes defined over family income, job loss, inflation, and more. The New York Fed's Survey of Consumer Expectations (www.newyorkfed.org/microeconomics/sce) includes questions with a similar structure and questions that elicit probabilities over multiple pre-specified outcomes, e.g., bins defined by inflation rate intervals. See Armantier et al. (2017).

Our core survey questions elicit five-point subjective probability distributions over each firm's own future sales growth, employment, and capital expenditures. The look-ahead horizon is four quarters or twelve months, depending on the outcome variable. Survey respondents freely select five support points and then assign probabilities to each. This approach affords great flexibility for the respondent, allowing for high or low expected growth, uncertain or predictable outlooks, and negative or positive skew in the distribution over future outcomes. It also avoids anchoring, because our question format specifies neither the location nor spread of the support points. Respondents nearly always update their subjective distributions across consecutive surveys, usually by modest amounts. This result suggests that they are attentive to the survey and actively update their responses as their perceptions change over time.

Using the subjective probability distributions, we measure expected future outcomes and the uncertainty surrounding those outcomes for each firm. Since the SBU includes questions about past and current outcomes, we can readily relate subjective forecast distributions to realized outcomes. Growth rate expectations are highly predictive of realized growth rates in the firm-level data, even after conditioning on firm and time fixed effects. Subjective uncertainty is highly predictive of absolute forecast errors. In addition, when firms express greater uncertainty about future outcomes, they make larger forecast revisions in the future. So, what drives subjective uncertainty? We show that it exhibits a pronounced V-shaped relationship to the firm's recent past growth, echoing similar results in Bachmann et al. (2018) and Bloom et al. (2017). Exploiting the panel dimension of the SBU, we also show that subjective uncertainty rises with the size of the firm's most recent forecast revision. Barrero (2020) provides additional evidence on the properties of the subjective probability distributions in SBU data, which we summarize in Section 3.

We also use SBU data to construct time series of the cross-firm average subjective expectations of employment growth, sales growth, and investment rates and the corresponding average subjective uncertainty levels. We began publishing these indices in November 2018 at www.frbatlanta.org/research/surveys/business-uncertainty, and they are now carried by Haver Analytics, Bloomberg, and the St. Louis Fed's FRED database (https://fred.stlouisfed.org/series/ATLSBUSGUI).

The SBU differs from earlier surveys of beliefs and expectations in key respects: an innovative question design for eliciting subjective probability distributions, a focus on outcomes at the respondent's own firm, a monthly sampling frequency, and broad coverage of the U.S. nonfarm private sector. For example, the quarterly Duke CFO Survey elicits perceptions of aggregate uncertainty in the form of 80 percent confidence intervals for future S&P 500 returns and, more recently, for U.S. GDP growth.[3] See Ben-David, Graham, and Harvey (2013) and cfosurvey.org. Surveys in Germany and Japan collect data on the expectations of firm-level variables. See Bachmann and Elstner (2015), Massenot and Pettinichi (2018), Tanaka et al. (2019) and Chen et al. (2019). While these surveys do not elicit subjective probability distributions, the ifo Business Tendency Survey collects quarterly data on the best- and worst-case sales growth scenarios of German firms (Bachman et al., 2018). The closest forerunner to the SBU is the Bank of Italy's Survey on Investment in Manufacturing, which has elicited subjective probability distributions at an annual frequency for decades (Guiso and Parigi, 1999). The SBU is also closely

[3] In 1947, the U.S. Department of Commerce and the Securities and Exchange Commission began fielding a quarterly survey that elicited point forecasts of firm-level sales and capital expenditures (Friend and Bronfenbrenner, 1955). The survey evolved over time, migrated to the Census Bureau, and ended in 1996 for budgetary reasons. The Empire State Manufacturing Survey has elicited forecast densities for firms' input price changes since 2009. See, for example, Federal Reserve Bank of New York (2013).

related to the Atlanta Fed's monthly Business Inflation Expectations (BIE) Survey. We conducted our initial field testing of SBU questions as part of the BIE's special question series.

Although a young survey, the SBU approach to eliciting subjective probability distributions from business managers has already been adopted in several other surveys with large-scale institutional backing. The U.S. Census Bureau put questions with the SBU design to about 50,000 manufacturing plants as part of the Management and Organizational Practices Survey (Bloom et al., 2017). Since August 2016, the Bank of England and University of Nottingham have fielded a monthly U.K. Decision Maker Panel Survey that follows the SBU closely, and which has proved especially useful in assessing business expectations and uncertainty related to Brexit (Bloom et al., 2018a). The British Office for National Statistics put questions that follow the SBU design to about 25,000 firms in 2017 as part of the new U.K. Management and Expectations Survey (Awano et al., 2018). Statistical agencies in China and Japan have also developed and fielded surveys of business managers that incorporate the SBU question design for eliciting subjective probability distributions over own-firm and aggregate outcomes.[4]

We enhance the value of the SBU by collecting additional information from our survey participants alongside our core data on past, current, and future outcomes. Special questions each month elicit (a) subjective probability distributions over other firm-level or aggregate outcomes, (b) information about the firm's characteristics or information processes, or (c) the perceived effects of specific economic and policy developments on the firm's own outcomes. In February

[4] The China Employer-Employee Survey (CEES) fielded SBU-type questions to 1,700 manufacturing firms in 2018 and is slated to gather the corresponding realizations in 2020. See Section 2 in Bloom et al. (2018b) for a description of the CEES. The Social Research Institute of Japan put three-point versions of the SBU questions to managers at about 13,600 manufacturing plants in 2017 and is now planning a second wave. Japan's Research Institute of Economy, Trade and Industry used the SBU question design in a 2017 survey to elicit subjective probability distributions over own-firm and aggregate outcomes. These Japanese surveys are not yet the subject of a paper in circulation, to our knowledge.

2018, for example, we asked whether and how the 2017 Tax Cut and Jobs Act caused firms to revise their capital investment plans for 2018 and 2019. In 2019, we posed several questions about the past and prospective effects of trade policy developments on investment, employment and sales. Aggregating over the firm-level responses to these questions yields survey-based estimates for the causal effects of policy developments. See Altig et al. (2019bc).

Section 1 describes the SBU and our approach to eliciting subjective forecast distributions. Section 2 explains how we measure firm-level expectations, uncertainty, and forecast errors. Section 3 relates subjective beliefs to future outcomes, forecast errors, and past outcomes. It also provides information about how firms update their beliefs over time. Section 4 presents activity-weighted average measures of business expectations and uncertainty. Section 5 presents additional results, including evidence that the shape of SBU subjective forecast distributions has predictive value for realized growth rates and the sign of forecast errors.

1. The Survey of Business Uncertainty

A. Core Question Design

The SBU elicits subjective probability distributions from business executives about own-firm future outcomes. To fix ideas, consider a discrete probability distribution over, say, the future sales growth rates of a firm. Suppose the distribution has N support points, $\{SaleGr_i\}_{i=1}^{N}$, with associated probabilities $\{p_i\}_{i=1}^{N}$. Given survey response values for these support points and probabilities, we can calculate the respondent's (mean) expectation of the sales growth rate as

$$Mean(SaleGr) = \sum_{i=1}^{N} p_i \cdot SaleGr_i \qquad (1)$$

and his or her subjective uncertainty as the standard deviation,

$$SD(SaleGr) = [\sum_{i=1}^{N} p_i(\, SaleGr_i - Mean(SaleGr) \,)^2]^{1/2}. \qquad (2)$$

Of course, we don't know how respondents conceptualize future growth rate possibilities. They may think in terms of fewer or more support points, or in terms of a continuous distribution. Subjective distributions are also likely to differ greatly across respondents in terms of location, scale, and shape and perhaps over time for individual firms. These observations argue for a question design that gives much flexibility to the respondent. In this regard, note that discrete distributions with few support points are highly flexible. A distribution with N=5 allows nine degrees of freedom (since the probability values sum to 1), more than enough to approximate most common parametric distributions. It also accommodates symmetric and asymmetric, single- and multi-mode, thin and fat-tailed distributions and those with wide or narrow support.

Several other considerations figure in our thinking about SBU question design. First, we require questions that respondents can comprehend and answer without undue burden. Much of our field testing and early analysis of survey responses focused on comprehension, as discussed in (Online) Appendix B. In addition, we conducted face-to-face cognitive interviews with small groups of SBU panel members (4-6 respondents per group), which also helped us assess comprehension. Second, business executives place a high value on their time. Thus, we aim for a short survey instrument with an average completion time of about five minutes. To help meet this goal, we split the panel into three groups, each of which rotates through the full set of core questions every three months.[5] One group gets the employment questions in any given month, one gets the sales questions, and one gets the investment questions. Third, the SBU is a self-administered, web-based survey, which requires questions that elicit answers without intervention by an enumerator or other survey representative.

[5] Early on, we split the panel into two groups and asked more questions each month. We shifted to the three-group design in May 2019 to maintain short response times. See Appendix B for details.

These considerations led us to a survey instrument in which respondents freely assign values to five discrete support points and then assign probabilities to each. Figures 1a and 1b display the core SBU employment and sales growth questions. Appendix A displays the investment questions. For each topic, the survey first asks for the current outcome in levels. Next, it asks about recent past outcomes – e.g., employment twelve months ago or the sales growth rate over the past twelve months. Then it asks the respondent to specify five future outcomes, ranked from lowest to highest, looking twelve months ahead for employment and from the current quarter to four quarters hence for the sales growth rate. Finally, the survey elicits probabilities for each of the five respondent-provided support points on the subjective distribution.

A series of field tests and cognitive interviews before launching the SBU revealed that business decision makers are willing and able to express beliefs about their firm's outlook in terms of discrete probability distributions with freely chosen support points. We began a new round of cognitive interviews in late 2019 to gather information about forecasting methods in use by our panelists and to solicit their thoughts about our survey instrument. Forecasting methods vary across firms but typically rely on some combination of the firm's sales history, conversations with key customers about anticipated product demand, and attention to industry trends and policy developments that could affect demand or costs. Interviewees report little difficulty in answering our forecast distribution questions, even when their internal forecasting methods do not parallel our question design. This pattern fits with longstanding evidence that consumers can express uncertainty about future events using subjective probabilities (e.g., Manski, 2004).

Our approach accords well with how business managers are taught to conceptualize uncertain future outcomes. To document this claim, we reviewed three top-selling textbooks in corporate finance, a subject with heavy enrollments in business schools. Nearly 75 percent of the examples and exercises about risk or uncertainty in these books specify discrete scenarios or probability distributions to formalize uncertainty.[6] Since more than 70 percent of our panel members are CEOs, CFOs, or have some other finance-related title, most are likely to be comfortable conceptualizing uncertainty in a manner that relates easily to our question design.

Many surveys that elicit subjective probability distributions over future economic outcomes use pre-specified bins or support points, as in the Philadelphia Fed's Survey of Professional Forecasters. That approach may work well when survey designers and respondents have a common understanding about the plausible range of outcomes for the variable of interest, say GDP or the firm's input costs. However, it is ill-suited for forecasts of firm-level growth rates, given the large differences in the central tendency and dispersion of their growth rates.[7] Our approach also avoids anchoring effects associated with pre-specified ranges or support points. By allowing free choice of support points and probabilities, we also let the respondent determine the shape of the forecast distribution. In contrast, Bachmann et al. (2018) create subjective distributions by imposing a triangular shape from "lowest" to "highest" scenarios.

Ours is not the only question design that gives flexibility to the respondent, accommodates great heterogeneity in subjective distributions, and avoids anchoring. The "unfolding brackets"

[6] The three textbooks are *Principles of Corporate Finance* by Richard A. Brealey, Stewart C. Myers; *Corporate Finance* by Stephen Ross, Randolph Westerfield, Jeffrey Jaffe and Bradford Jordan; and *Corporate Finance* by Jonathan Berk and Peter DeMarzo. The second most-common approach uses a parametric distribution with one or two parameters, which is not flexible enough for our purposes.

[7] Caves (1998) and Davis and Haltiwanger (1999) review and add to an extensive literature documenting large differences in the central tendency and dispersion of business growth rates by industry, size, and age. Bloom et al. (2017) show that managers' expectations and subjective uncertainty fall sharply with size and age and rise with the past volatility of the establishment, its parent firm, and its industry. In principle, a survey designer could condition on all these factors to tailor pre-specified bins that vary by firm and time. Even when rich data of this sort are available, however, senior executives have more information about own-firm growth prospects and risks than survey designers. Moreover, it is unclear how a survey designer should adjust bins in the wake of unusual or extraordinary shocks, e.g., the 2020 coronavirus pandemic. Letting respondents freely select support points and probabilities respects firm-specific information without requiring that survey designers possess such information.

approach presents survey respondents with a sequence of questions to elicit quantiles of the subjective distribution. For example, one can first pose a question that elicits the median of the subjective distribution over the growth rate of future sales, then pose two questions to elicit the 75th and 25th percentiles, and so on. See, for example, Juster and Suzman (1995) and Hurd (1999). Relative to unfolding brackets, our approach offers two advantages. First, it yields a shorter survey instrument with fewer questions. Eliciting five quantiles via unfolding brackets requires a sequence of five questions, whereas our design elicits a five-point distribution in two questions. Given our respondents are senior executives, a longer survey would tax their patience further and likely lower response rates and sample retention. Second, as noted above, our approach aligns well with how managers are taught to conceptualize uncertainty in terms of scenario planning.

We close our discussion of question design with a detail that has important effects on response accuracy. Our forward-looking questions elicit beliefs about the *level* of future employment but the *growth rate* of future sales. Respondents tend to think in these terms. Moreover, field testing revealed that asking about the level of future sales yields more response errors of two types: adding or dropping a digit when entering values for support points, and the inconsistent use of units across surveys – or even in the same survey. For example, a respondent might switch from quarterly to annual sales or thousands to millions of dollars. While we developed methods to detect and correct these sorts of response errors, we also experimented with question formulation to reduce the incidence of such errors. As of September 2016, we settled on a formulation that asks about past and future sales growth rates and the level of sales in the current quarter. Appendix A presents earlier incarnations of our sales-related questions.

B. Sampling, Panel Recruitment, and Response Rates

We obtain lists of randomly selected firms and their senior executives from an affiliate of Dunn & Bradstreet, a supplier of business information and research. In turn, we sample from these lists to recruit panel members, working with a team of research assistants at the Atlanta Fed. We aim for a panel of firms that is reasonably well balanced across industries and regions. We deliberately oversample larger firms and, to a lesser extent, firms in cyclically sensitive industries. The recruitment process continues, as we build and refresh the SBU panel over time. Each month, we deliver the survey link to panel members via email and let them fill it out over a two-week period on their own time.

During the period from June 2014 to June 2018, approximately 42 percent of potential contacts reached via telephone agreed to join the panel. Among those who joined, 62 percent responded to the survey at least once. In any given month, about 43 percent of continuing panel members respond to the survey.[8] These high response rates in a voluntary survey of business executives reflect the resources we devote to sample recruitment and maintenance. As of August-October 2019, we receive about 360 completed survey responses per month. The median survey completion time is 4.4 minutes, and the mean is 7.6 minutes.[9] See Appendix A for more information about recruitment and response rates.

C. Survey Development, Testing, Data Cleaning, and Sample Mix

We began fielding trial SBU questions in October 2013 as part of the Atlanta Fed's monthly Business Inflation Expectations (BIE) Survey, which samples firms in the Sixth Federal Reserve

[8] These response rates refer to the period from September 2016 (the last major change in core survey questions) to October 2018.

[9] These statistics pertain to the period since May 2019, when we began asking about only one core topic (sales, employment, or investment) per panel group per month. Median and mean survey completion times before May 2019 are 5.5 and 8.7 minutes, respectively. In computing these statistics, we winsorize completion times at the 90th percentile to deal with respondents who open the survey tool and set it aside for a spell (possibly days) before returning to the tool and completing their responses.

District (Florida, Georgia, Alabama, and parts of Tennessee, Mississippi, and Louisiana). In July 2014, we launched the SBU as a separate national survey, originally known as the Decision Maker Survey. Over the past six years, we experimented with several aspects of our question design: pre-selected support points, fewer support points, interval bins in place of support points, fixed probabilities for respondent-chosen support points or bins, and other matters. We also fielded questions that elicit subjective probability distributions over future profit margins and unit cost growth. While the profit margin and unit cost questions yield interesting data, they are hard to formulate in a uniform manner that works well across all industries. Their inclusion also makes it harder to meet our completion-time targets, so we ultimately dropped them from our core instrument. See Appendix B for a more detailed discussion of SBU survey development and testing. The last major change to the core SBU questions occurred in September 2016.

The SBU sample covers all 50 states, all major nonfarm industries, and a range of employer size categories, as documented in Appendix A. Relative to the industry distribution of nonfarm private employment, the SBU sample materially over represents Durable Manufacturing and Finance & Insurance. It under represents Health Care & Social Assistance and Leisure & Hospitality. The employment share of small firms in the SBU sample is much lower than in the U.S. private sector, especially for firms with fewer than 20 employees. The SBU covers very few firms less than five years old for three practical reasons: lags in the identification of new firms by Dunn & Bradstreet, our infrequent purchase of business lists for cost reasons, and lags in our sampling from the lists we purchase.

All SBU data are subject to automatic review and cleaning algorithms, with further manual review of extreme outliers. Firms with more than 1,000 employees undergo manual reviews as a matter of routine. Extreme outliers and potentially anomalous responses of large firms are evaluated for consistency with historical responses and publicly available information. When manual reviews are inconclusive, we may contact the respondent for clarification. See Appendix A for more information and Altig et al. (2019a) for a full discussion.

2. Measuring Subjective Expectations, Uncertainty, and Forecast Errors

This section explains how we use the raw SBU data to compute firm-level forecasts expectations, the subjective uncertainty around the forecasts, realized outcomes, and forecast errors. For the sake of concreteness, we focus on sales growth rates in describing the measurement mechanics. The mechanics differ somewhat for investment rates, as we discuss.

Each respondent supplies future sales growth rate values, $FSaleGr_i$, at support points $i = 1,2,3,4,5,$ and the associated probabilities, p_i. We interpret the $FSaleGr_i$ values as conventional growth rates – i.e., percent changes on the initial value. As a preliminary step, we re-express conventional growth rates as arc percentage changes using the formula, $SaleGr_i = \frac{2FSaleGr_i}{FSaleGr_i+2}$. This growth rate measure is symmetric about zero, bounded between -2 and 2, and equal to log changes up to a second-order Taylor series approximation. Growth rates computed in this manner aggregate exactly when combined with suitable weights, given by the simple mean of initial and (expected) terminal levels. This approach to growth rate measurement and aggregation is standard in the literature on business-level dynamics. See, for example, Davis and Haltiwanger (1999).

Given support points, $SaleGr_i$, and probabilities, p_i, we compute mean expectations and subjective uncertainty as in (1) and (2). We compute the realized growth rate from t to $t + j$ as

$$RSaleGr_{t,t+j} = \frac{Sale_{t+j} - Sale_t}{(1/2)(Sale_{t+j} + Sale_t)}, \qquad (3)$$

where $Sale_t$ is reported sales at t. The error in the q-quarter ahead forecast error at month t is

$$Err(SaleGr)_t^q = RSaleGr_{t,t+3q} - Mean(SaleGr)_t^q, \qquad (4)$$

where $Mean(Sales)$ is defined by (1). For employment, we compute arc percentage changes from the reported and forecasted employment levels.[10] When absolute forecast errors exceed one (approximately +200% or -66%) for sales or employment growth rates, we manually review the underlying responses and use the firm's history of responses to correct obvious mistakes such as missing or extra zeros, or the mixing of annual and quarterly sales figures. If we find no obvious mistake, we flag the observation as a likely response error and exclude it from our analysis of forecast errors.

In September and October 2017 and again in February and March 2019, we asked firms to report the book value of their capital stock (property, plant, and equipment). Starting in May 2019, we query firms every few months about book value capital stock. When available, we use the book-value capital stock as the denominator in the investment rate, I/K. When unavailable, we interpolate or extrapolate the capital stock based on the firm's reported values in other periods. If that, too, is unavailable, we use a regression-based imputation. The numerator values in the I/K ratio come directly from our core question about capital expenditures.

Table 1 reports descriptive statistics for the support points and corresponding probabilities in our SBU data. Mean outcomes vary widely across support points, ranging for example from -0.106 to 0.115 for 12-month employment growth rates. The mean probability mass assigned to the middle support point is about 40 percent for each outcome variable, with a mean mass of about 10 percent in each tail. Standard deviations are sizable for both support point and probability values. Table 2 reports summary statistics for forecast means, subjective uncertainty, and realized outcomes. The data exhibit considerable heterogeneity across firms in terms of realized outcomes,

[10] For sales growth rates (and investment rates), we work with observations that are j=4 quarters apart. For employment growth rates, we work with observations that are j months apart, where j ranges from 10 to 14. When $j \neq 12$, we re-state the employment growth rate in annualized terms.

forecast means, and subjective uncertainty. This heterogeneity is useful for analysis and reassuring in light of much previous work on the heterogeneity of realized firm-level outcomes.

3. Properties of Subjective Distributions, Uncertainty, and Forecast Errors

We now document several properties of the firm-level subjective forecast distributions. Our analysis sample covers SBU survey waves from October 2014 to October 2019. For the sake of brevity, we focus on results for sales growth rates. Results are very similar and often sharper for employment growth rates, as shown in Appendix C. Many qualitatively similar patterns hold for investment rates as well.

<u>Expected Growth Rates Predict Realized Growth Rates</u>

Figure 2 provides evidence that firm-level sales growth rate forecasts have predictive power for realized growth rates at a four-quarter look-ahead horizon. Panel (a) displays a bin scatter of firm-level values for $RSaleGr_{t,t+3q}$ in (3) against the corresponding four-quarter ahead expected growth rates at *t*, given by $Mean(SaleGr)_t^q$ in (1). It also reports the corresponding OLS regression run on the underlying firm-level data. The estimated slope coefficient on the expected growth rate is 0.59 with a firm-clustered standard error of 0.08, soundly rejecting the null of a unit slope coefficient. We are mindful, however, that measurement errors in the firm-level expected growth rates are likely to impart a downward bias in the OLS slope coefficient.[11] Indeed, using the value of the middle support point to instrument for the firm's expected sales growth rate yields a coefficient of 0.87 (0.13), insignificantly different from one. Alternatively, using the contemporaneous expected employment growth rate as an instrument yields a coefficient of 1.11

[11] Measurement errors can arise because the respondent's (mean) forecast is truly noisy, because our question design elicits a noisy representation of the respondent's true forecast distribution, or for more mundane reasons – e.g., a respondent who mistypes when entering support point values or probabilities.

(0.49). In short, IV regressions provide little evidence against the hypothesis of unbiased expectations. These results are consistent with Barrero (2020), who also finds little evidence of unconditional bias in firm-level expected growth rates using SBU data.

Firm-level expected sales growth rates continue to have predictive power for realized sales growth rates when we add controls for time and firm fixed effects, as shown in Panels (b) and (c) of Figure 2. The sample average of a firm's expected sales growth rate values also has strong predictive content for the average of its realized sales growth rates, as shown in Panel (d).

Subjective Uncertainty Predicts the Magnitude of Forecast Errors

Figure 3 provides evidence that subjective uncertainty, as measured by (2), is highly predictive of the absolute value of the forecast errors in (4). Panel (a) shows a strong, positive relationship in the raw data. Including time fixed effects has little impact on the fitted relationship, as seen in Panel (b). Including firm effects as well weakens the relationship, but still yields a positive, significant relationship of error magnitudes to uncertainty. In other words, changes in firm-level subjective uncertainty are predictive of changes in the magnitude of firm-level forecast errors. We conclude that our measure of subjective uncertainty captures more than persistent cross-firm differences in uncertainty. The cross-firm relationship of absolute forecast errors to subjective uncertainty is indeed a strong and prominent feature of the SBU data, as shown in Panel (d). Subjective uncertainty also falls with firm size and age, as shown in Appendix C. These patterns are reassuring, given that growth rate dispersion and volatility fall with firm size and age. See, for example, Davis and Haltiwanger (1992), Caves (1998), and Davis et al. (2006).

While there is strong evidence that subjective uncertainty predicts the magnitude of forecast errors, it does not follow that firms accurately perceive the (expected) magnitude of their errors. Barrero (2020) examines this issue using SBU data. To do so, he samples from the subjective forecast distributions to generate the implied distribution of forecast errors. This implied distribution is much narrower than the actual distribution of forecast errors: The average magnitude of actual forecast errors is four times larger than the average magnitude of implied errors. Barrero also shows that over confidence about forecast precision holds for large and small firms but tends to fall with firm size. Ben-David et al. (2013) find that CEOs are over confident about the precision of their forecasts of returns on the S&P 500. Taken together, these studies say that senior managers appear overconfident about their forecast precision with respect to developments at their own firms and in the broader economy.

Respondents Update Reported Beliefs Often, Usually by Small Amounts

We now investigate how individual respondents update their forecast distributions over time.[12] Table 3 shows that nearly all respondents provide a different forecast distribution in month *t* for each outcome than they provided 2 or 3 months earlier in their previous survey response. For example, 95.7 percent of sales growth responses involve different support points between nearest surveys, and 94.7 percent involve different probabilities. Over 99 percent of the sales responses in consecutive surveys imply revisions to the first and second moments of the subjective probability distributions. Clearly, respondents do not supply a "boilerplate" distribution each month without thinking. Instead, they nearly always modify their reported subjective probability distributions.

To get a handle on *how much* they revise reported beliefs, we compute the cosine similarity of their support point and probability vectors between nearest same-topic surveys. For any pair of vectors x and x' in $\mathbb{R}^n$, cosine similarity is the cosine of the angle between them:

[12] Reputational concerns and attention-seeking behavior can lead professional forecasters to distort their reported beliefs in ways that yield herding or extreme forecasts. See, for example, Lamont (2002) and Marinovic et al. (2013). Because SBU respondents are anonymous and forecast own-firm outcomes, there is no reason to anticipate such behavior in our setting. Thus, we focus on the frequency, magnitude, and character of forecast revisions.

$$\cos(\theta) = \frac{x' \cdot x}{\|x'\| \|x\|}$$

where "·" denotes the inner product and $\|x\|$ is the Euclidean norm of x. Cosine similarity ranges from -1 to 1. Two vectors pointing in exactly the same direction (for which $\theta = 0$) have $\cos(\theta) = 1$, orthogonal vectors have $\text{cosine} = 0$, and vectors pointing in exactly opposite directions have $\text{cosine} = -1$. Accordingly, higher cosine similarity means that two vectors are more similar in the geometric sense of pointing in more similar directions.

Table 4 reports the mean of cosine similarity values across surveys 2 or 3 months apart for the same firm. The mean cosine values are mostly between 0.84 and 0.89 and significantly different from 1. The cosine similarity of support points for future investment is larger at 0.976, yet still significantly different from one. Thus, we find clear evidence that respondents update their forecast distributions between surveys, while on average maintaining broadly similar responses (since the mean similarity is much closer to 1 than 0). For future investment, respondent support points are much more similar across nearest surveys. This result suggests that anticipated investment is revised less often than sales and employment growth expectations.

Table 5 quantifies the persistence of reported beliefs by fitting AR(1) models to subjective expectations and uncertainty of firm-level sales growth rates. The raw panel regressions in columns (1), (4), and (7) and the specifications with time fixed effects in (2), (5), and (8) show autocorrelations of just over 0.6 for subjective expectations, somewhat above 0.75 for subjective uncertainty, and about 0.66 for log-subjective uncertainty. These results suggest that shocks to firm-level sales growth rate expectations decay by about forty percent between nearest surveys and by about one-fourth to one-third for subjective uncertainty (in levels versus logs). Autocorrelations are smaller at about 0.25 or less when we also condition on firm effects, but still positive and statistically significant.

Subjective Uncertainty Predicts the Magnitude of Future Forecast Revisions

Having established that SBU respondents actively revise their reported beliefs, we next consider how subjective uncertainty relates to the magnitude of the firm's future forecast revisions. Figure 4 shows that firms reporting greater uncertainty today make larger future revisions to their expectations. The figure plots the absolute change in the sales growth rate expectation from *t* to *t+2* (or *t+3*) against subjective uncertainty about the sales growth rate at *t*. The positive relationship between a firm's subjective uncertainty today and the magnitude of its future expectation revision holds in the raw data and when controlling for firm and time fixed effects.

Figure 5 shows that a firm's current subjective uncertainty is also predictive of future revisions to its subjective uncertainty. The figure plots the absolute change in a firm's sales growth rate uncertainty from *t* to *t+2* (or *t+3*) against subjective uncertainty about its sales growth rate at *t*. Again, the positive relationship holds in the raw data and when controlling for firm and time fixed effects. Perhaps surprisingly, firm-level uncertainty at *t* has even more predictive power for the magnitude of future revisions to the firm's uncertainty than for the magnitude of future revisions to its expectation.

Do Revisions in Expectations Predict Future Forecast Errors?

We now consider whether revisions in a firm's expectations predict its future forecast errors, following Coibion and Gorodnichenko (2015). In particular, we regress the error in the sales growth rate forecast formed at t in equation (4) on a constant and same-firm changes in $Mean(SaleGr)^q_{t-j} - Mean(SaleGr)^q_t$, for $j = 2$ or 3. The regression, which has 2,177 firm-level observations, yields a slope coefficient of 0.335 (0.09) and an R-squared value of 0.008. The positive slope suggests that business executives over extrapolate from recent news in forming expectations about the future growth of their firms. They are both too optimistic in the wake of good news, and too pessimistic in the wake of bad news.

Measurement error in the reported expectations could also drive the positive slope coefficient in this regression. In this regard, note that $Mean(SaleGr)_t^q$ enters both the dependent and independent variables in the regression. Partly motivated by concerns about measurement error, Barrero (2020) presents a broader range of tests and concludes that over extrapolation is a feature of managerial beliefs in SBU data. Gennaioli, Ma and Shleifer (2016) present evidence that points to over extrapolation in the expectations reported in the Duke Survey of CFOs.

Subjective Uncertainty Has a V-shaped Relation to Past Growth and Forecast Revisions

Subjective uncertainty is associated with larger revisions in future beliefs (Figures 4 and 5), but what shapes subjective uncertainty? To throw light on this matter, Figure 6 displays two bin scatters with $SD(SaleGr)_t^q$, uncertainty about the q-quarter ahead forecast at t, on the vertical axis. Panel (a) relates this measure of subjective uncertainty to $RSaleGr_{t-12,t}$, the realized sales growth rate over the previous year. Firms with greater absolute growth rates in the past year report higher subjective uncertainty, yielding a pronounced V-shaped pattern. This result is consistent with models in which firms have stochastic volatility – they go through periods of higher and lower volatility. Large recent shocks in these models are associated with higher levels of current volatility, and hence higher future uncertainty.

We can assess this stochastic volatility interpretation directly by exploiting the panel structure of the SBU. To do so, panel (b) in Figure 6 relates subjective uncertainty at t to the absolute value of the firm's most recent expectation revision given by $\left|Mean(SaleGr)_{t-j}^{q} - Mean(SaleGr)_{t}^{q}\right|$, for $j = 2$ or 3. Again, we see a pronounced V shape.[13]

Next, we nest these two effects in a single regression model. Specifically, we regress subjective uncertainty at *t* on a constant, the firm's absolute growth rate over the previous year, and the absolute value of its most recent expectation revision. This regression, which has 4,722 observations, yields a coefficient of 0.119 (0.012) on $\left|RSaleGr_{t-12,t}\right|$ and a coefficient of 0.228 (.025) on $\left|Mean(SaleGr)_{t-j}^{q} - Mean(SaleGr)_{t}^{q}\right|$, for $j = 2$ or 3. The R-squared value is 0.362. That is, subjective uncertainty rises with the firm's absolute growth rate in the recent past *and* with the magnitude of its recent forecast revisions. Using employment counterparts to the sales measures yields very similar regression results, with an R-squared value of 0.336. These results say that subjective uncertainty is high in the wake of large recent changes to the firm's activity level and in the wake of large revisions to its future growth prospects. Both effects are present in the data, and neither drives out the other in our regression specifications.

4. Indices of Business Expectations and Uncertainty for the US Economy

This section describes how we use SBU data to construct indices of business expectations and uncertainty. Our basic approach is to compute size-weighted averages of first and second moments in the firm-level subjective forecast distributions. As before, the look-ahead horizon is twelve months for employment growth and four quarters for sales growth and investment.

In constructing the indices, we winsorize firm-level mean forecasts and subjective uncertainty values at the 1st and 99th percentiles in the fixed period from January 2015 to December

[13] In unreported results, subjective uncertainty at *t* also has a V-shaped relation to the error in the sales growth rate expectation formed one year-earlier. This relationship is noisier than the ones shown in Figure 6 and is derived from a smaller sample.

2018. In averaging the winsorized values over firms, we weight by the firm's employment level, top coded at 500. The top coding of activity weights reflects our judgment based on long experience in analyzing business-level data. Outliers and errors for large firms can seriously distort sample-average quantities, more so for samples of modest size and for higher-order moments.

Figure 7 displays smoothed expectation and uncertainty indices for sales and employment growth rates. We plot these measures from January 2017, owing to changes in the survey data from September 2016 onwards and our use of three-month lagged moving averages.[14] The first-moment indices in the left panel show that expected one-year growth rates dip in mid-2017 and then rise through early 2018 for employment and through late 2018 for sales, reaching 5 percent near the end of 2018. Growth rate expectations fall thereafter but stay above 1 percent for employment and near 4 percent for sales until COVID-19 hits in March 2020. Expected growth drops sharply as the pandemic unfolds, reaching a trough in May 2020. As of August 2020, year-ahead sales growth expectations remain low relative to the history of the series at about 1.5 percent, while employment growth expectations are close to their 2018 level. These values suggest firms in the SBU expect a slow and only partial recovery from the staggering losses in revenue and employment that characterize the 2020 pandemic recession.

The second-moment indices in the right panel show that subjective uncertainty stays close to 3 percent for sales and 4 percent for employment from early 2017 until COVID-19 hits in March

[14] First, we expanded the sample significantly in mid-2016. Second, we modified the panel rotation scheme in September 2016, which raised the number of respondents per topic from about 50 to 150. The aggregate series are much noisier before this change. Third, we revised the formulation of our sales questions in September 2016, which markedly reduced response errors and the noisiness of aggregate measures. For these reasons, we refrain from splicing the aggregate measures before and after January 2017, although we retain the data for earlier months in our research database. Appendix D shows our aggregate measures for I/K. They are noisier than the sales and employment measures due to the lumpiness of firm-level investment, our heavy use of imputed values for firm-level capital stocks, and possible weaknesses in our question design for capital expenditures.

2020. Subjective uncertainty peaks at nearly 200 and 140 percent of its pre-pandemic average, respectively, for sales and employment. As of August 2020, employment growth and sales growth uncertainty remain highly elevated.

The stability of our subjective uncertainty measures from early 2017 until early 2020 may seem surprising in light of the extraordinary rise in trade policy uncertainty after March 2018. (Baker, Bloom and Davis (2019) review several pieces of evidence). As part of our special question series, we asked SBU panel members about trade policy developments in January, July, August and September of 2019. The resulting data show mounting concerns about tariff hikes and trade policy tensions and evidence of their negative effects on employment, sales and investment. The effects are modest in size, however, and a majority of SBU panel members report little direct exposure to trade policy developments (Altig et al., 2019bc). Taken together, Figure 7 and our earlier reports suggest two conclusions. First, other sources of business-level uncertainty diminished after early 2018, muting or offsetting the impact of rising trade policy uncertainty. Second, trade policy developments contributed to the falling growth rate expectations in 2018 and 2019. We are, however, reassured that our first and second moment indices both reflect the enormous COVID-19 shock to the US economy.

To our knowledge, there are no alternative time-series measures for the United States that quantify the same concepts as our SBU indices. So, we turn to some admittedly imperfect comparisons. The Duke University Survey of CFOs at U.S. firms includes the following question: “Relative to the previous 12 months, what will be your company’s PERCENTAGE CHANGE [in revenues] during the next 12 months. (e.g., +3%, 0%, -2%, etc.)?” That is, the Duke survey elicits the expected *change* in growth rates from the past year to the year ahead. In contrast, the SBU yields the expected growth rate in the year ahead. Nevertheless, one might expect the two surveys to yield positively correlated first-moment indices. That turns out to be the case, as seen in the left panel of Figure 8. We plot the revenue-weighted mean in month *t* of firm-level responses to the Duke survey question above alongside our SBU sales growth rate expectations index at *t*. The two series exhibit broadly similar movements over our sample period, including a steep drop in expectations in 2020 as the COVID-19 pandemic recession unfolds.

The right panel in Figure 8 shows our sales growth uncertainty index alongside a smoothed version of the one-year-ahead VIX, which measures the volatility of the S&P 500 implied by options set to expire one year hence.[15] We focus on the VIX because it is well known, widely used, and often seen as a proxy for broad economic uncertainty. In fact, the VIX is better understood as measuring the expected magnitude over the option horizon of news about the stock market value of larger, listed firms.[16] Despite the conceptual differences, Figure 8 reveals that our uncertainty index correlates positively with the VIX, especially in 2020 when both series jump to historic highs (within our sample period) with the arrival of the COVID-19 pandemic.

The comparisons in Figure 8 suggest that our SBU indices respond to economic developments in a manner that is broadly similar to other model-free indicators of expected growth rates and economic uncertainty, namely the Duke CFO Survey and the VIX. Like the SBU, these other sources are available in (near) real time and, in the case of the Duke Survey, pertain to forecasts of own-firm outcomes.

[15] Since the SBU is in the field during the second and third week of the month, we take the value of the one-year VIX on the 15th of the month. If the 15th is not a trading day, we use the 16th, 14th, 17th, 13th, 18th, or 12th in that order. We smooth the resulting monthly one-year VIX series using the same procedure as for our SBU indices.

[16] These firms account for about a quarter of private sector employment, and they differ systematically from the economy as a whole on several dimensions. In particular, listed firms skew toward bigger, older, capital-intensive, skill-intensive and multinational firms. See Davis (2017). Changes in the mix of listed firms and their leverage choices also affect the VIX.

In closing this section, we wish to stress the preliminary nature of our SBU indices. The current SBU sample is modest in size and excludes younger firms. We continue to expand the sample and refine our methodology and data auditing and cleaning methods. Like any startup survey, we need many years (or large in-sample moves) before we can confidently assess the predictive value of the aggregate SBU indices. Nevertheless, the predictive value of our firm-level subjective forecast distributions, as documented in Section 3, provides grounds for optimism in this regard.

5. Additional Results and Robustness Checks

The Shape of SBU Forecast Distributions Has Predictive Value

Section 3 shows that first and second moments of SBU forecast distributions have predictive value for realized future growth rates (Figure 2), the magnitude of future forecast errors (Figure 3), and the extent of future forecast revisions (Figures 4 and 5). We now investigate whether other aspects of SBU forecast distributions – beyond first and second moments – have predictive value for firm-level outcomes.[17]

We first ask how skewness in subjective forecast distributions relates to skewness in realized outcomes over the forecast horizon. To do so, we sort the firm-level observations into quartiles defined by the Fisher-Pearson skewness coefficients of the subjective forecast distributions. For each quartile, we compute the mean value of the subjective skewness coefficients and the skewness coefficient of realized growth rates over the forecast horizon. Figure 9 displays a scatter plot of these two measures. For employment growth rates, skewness in realized outcomes

[17] The skewness of cross-sectional outcomes is known to covary in interesting ways with aggregate outcomes. See, for example, Guvenen et al. (2014) on cyclicality in the skewness of individual-level earnings shocks and Salgado et al. (2019) on the cyclicality of skewness in firm-level growth rates.

rises strongly with prior subjective skewness. For sales growth rates, the relationship is similar except for the anomalous second quartile. Overall, Figure 9 suggests that skewness in the subjective forecast distribution portends skewness in the distribution of realized outcomes.[18]

Finally, Appendix C shows that the third moment of SBU forecast distributions has predictive value for realized growth rates and the absolute value of forecast errors when conditioning on the first two subjective moments. This pattern holds for both sales and employment growth rates and is especially strong for sales. While interesting as more evidence that the shape of SBU forecast distributions has predictive value for firm-level outcomes, the interpretation is unclear. One interpretation is that skewness is also an important driver of firm and aggregate growth (e.g. Salgado, Guvenen and Bloom, 2019).

In summary, we find strong evidence across various exercises of predictive content in the shape of SBU forecast distributions over employment growth rates. The evidence of predictive content in the shape of SBU forecast distributions over sales growth rates is weaker. We leave it for future research to explain why.

Do Repeat Applications of the Survey Instrument Affect Responses?

Repeated application of a survey instrument can influence how a respondent thinks about the survey questions, affecting his or her responses over time. Binder (2019), for example, finds that inflation forecasts and inflation uncertainty decline with the number of previous responses among participants of the New York Fed's Survey of Consumer Expectations. Patterns like these raise questions about how to interpret the survey data and their properties.

[18] We also regress the sign of the forecast error in (4) on a constant and the fraction of the forecast distribution on support points greater than $Mean(SaleGr)_t^q$. This should be positive if the subjective and true distributions are the same. For sales this regression is positive but insignificant: coefficient 0.034 (standard error 0.051). For employment growth this is significant: coefficient 0.089 (standard error 0.046).

To investigate this matter in the SBU, we regress the natural logarithm of subjective uncertainty on the respondent's number of previous survey completions as of month t.[19] We control for time effects, because the average number of completions among respondents at t covaries with calendar time. We include firm effects to isolate within-firm variation. The results, reported in Table 6, reveal no statistically significant evidence of survey application effects. Moreover, the point estimates imply tiny effects. For example, the coefficient in column (2) says ten previous survey completions lowers the log of subjective uncertainty by -0.03. This effect is about 1 percent of the dependent variable mean value and 3 percent of its standard deviation. Unreported results for mean expectations also reveal no evidence of survey application effects.

Figure 10 reports results for a nonparametric specification that allows an unrestricted relationship between the firm's reported value of log subjective uncertainty and its number of previous completions. As before, we include firm and time fixed effects in the specification. As seen in the left panel of Figure 10, there is weak evidence of small negative survey application effects when we do not activity weight the firm-level observations. The effect appears to settle in over about nine completions and then stabilize at a value about 5-6 percent as large as the mean of the dependent variable and 20-25 percent of its standard deviation. The activity-weighted results in the right panel of Figure 10 show no indication of survey application effects.[20]

In summary, Table 6 and Figure 10 support three inferences. First, there is little evidence against the null that repeated survey applications have zero effect on survey responses. Second, the point estimates imply tiny survey application effects. Third, large survey application effects

[19] Logging yields a more normally distributed outcome variable, but similar results hold when using unlogged subjective uncertainty as the dependent variable.

[20] This pattern suggests that repeated application of the survey instrument has modest negative effects on the subjective uncertainty reported by small firms.

are quite unlikely, given the precision of the point estimates. We conclude that survey application effects on reported responses are not a major concern in the SBU.

The Impact of Replacing Discrete with Continuous Distributions

To this point, we have interpreted survey responses literally in calculating subjective moments. As remarked in Section 1.A, we don't know how respondents conceptualize uncertainty. Instead of a mass point at the "worst" case in a five-point distribution, for example, the respondent might contemplate a range of bad outcomes. Rather than a discrete distribution, respondents might think in terms of continuous or mixed distributions. To get some sense of whether this issue matters much, we now interpret responses as approximations to an underlying continuous distribution.

Let g_i and p_i denote support points and probabilities in the raw survey data for $i = 1,2,3,4,5$. Assume that these survey responses derive from the following continuous density:

$$f(x) = \begin{cases} \dfrac{p_1}{g_2 - g_1}, & \text{for } x \in \left[\dfrac{3g_1 - g_2}{2}, \dfrac{g_1 + g_2}{2}\right), \\ \dfrac{p_i}{(g_{i+1} - g_{i-1})/2}, & \text{for } x \in \left[\dfrac{g_{i-1} + g_i}{2}, \dfrac{g_i + g_{i+1}}{2}\right), \qquad i = 2,3,4, \\ \dfrac{p_5}{g_5 - g_4}, & \text{for } x \in \left[\dfrac{g_4 + g_5}{2}, \dfrac{3g_5 - g_4}{2}\right]. \end{cases} \tag{5}$$

Equation (5) specifies five adjoining uniform density segments. The leftmost segment is centered at g_1, the "worst" forecast outcome in the raw survey data. It extends leftward from g_1 by $(g_1 - g_2)/2$ units and rightward by $(g_2 - g_1)/2$. Given its length, the height of the density segments is selected to exhaust, p_1, the mass assigned to the "worst" outcome in the raw data. The next segment extends from $(g_1 + g_2)/2$ to $(g_2 + g_3)/2$ and so on, with the height of each density segment selected to exhaust the corresponding mass point in the raw data. In other words, equation (5) takes the mass assigned to each support point in the raw data and spreads it uniformly in a symmetric interval around the support point.

Figure 11 compares the first and second moments generated from (5) to the corresponding moments computed directly from the SBU data. The two approaches to moment calculation yield nearly identical results over almost the entire range of sales growth rates in the data. Only for the 1st and 99th quantiles of log subjective uncertainty do we see notable deviations between the discrete and continuous interpretations of the data. In Appendix C, we also show that continuous and discrete interpretations of SBU data perform equally well with respect to the predictive value of mean expectations for realized growth rate outcomes. The discrete interpretation performs slightly better with respect to the predictive value of subjective uncertainty for the magnitude of absolute forecast errors. These results suggest that the five-point probability distributions elicited by the SBU are not an important source of approximation errors.

How Do Sample Composition Changes Affect Our Expectation and Uncertainty Indices?

The SBU is a panel survey with entry and attrition over time. That raises the possibility that sample mix changes could materially impact movements in the first- and second-moment indices in Section 4. To explore this matter, we fit employment-weighted regressions of the form,

$$y_{ft} = \alpha_f + \beta_t + \varepsilon_{ft}, \tag{6}$$

where y_{ft} is a measure of growth rate expectations or subjective uncertainty for firm f in month t, α_f is a vector of firm fixed effects, and β_t is a vector of time effects. The estimated β_t constitute a time series of employment-weighted outcomes that control for changes in the mix of firms in the sample. Dropping α_f in (6) and refitting an employment-weighted regression, the estimated β_t recover the original indices described in Section 4.

Figure 12 displays the results of fitting (6) – with and without firm fixed effects – for sales growth rate expectations and subjective uncertainty about sales growth rates. Controlling for sample composition has little effect on our indices. [21]

Reweighting to Match the Industry and Regional Distribution of Activity

Another set of issues relates to sample representativeness. An unrepresentative sample may yield biased estimates of population moments. Moreover, because the SBU oversamples cyclically sensitive industries, common shocks may generate larger responses of the (activity-weighted) average subjective forecast distributions in the sample than in the economy. To investigate these issues, we reweight the firm-level observations in the SBU sample to target the distribution of activity by industry and region in the U.S. economy. We then use the reweighted data to construct alternative indices. Appendix D explains how we reweight, presents the alternative indices, and compares them to the baseline indices in Figures 7 and 8.

Since 2017, the alternative and baseline indices differ by only about 10 basis points for the average expectation of employment growth rates and by only 8 to 10 basis points for the corresponding average subjective uncertainty. A similar pattern holds for the sales growth rate measures, but modest gaps persist: in particular, reweighting lowers the average expectation (subjective uncertainty) of sales growth rates by about 31 (20) basis points. Happily, reweighting has little impact on the cyclical behavior of the sales growth rate uncertainty index. The same is true for the sales growth rate expectations index. The alternative indices are often noisier than the baseline indices, a consequence of upweighting firm-level observations in thin cells.[22] To sum up,

[21] Unreported results show that controlling for sample composition has a larger, but still modest impact on the evolution of the expectations and uncertainty indices prior to 2017. In this regard, we note that our sample size increases roughly three-fold after mid-2016. Over time, it also becomes more representative of the US industry distribution. These sample improvements explain why composition effects are smaller after September 2016.

[22] Recall that we have only about 150 observations per month per outcome variable after September 2016, and a mere 50 observations before that.

the representativeness of the SBU sample appears adequate for drawing reliable inferences about business expectations and uncertainty in the U.S. economy from January 2017 onwards.

Concluding Remarks

We develop and field a new panel survey of business executives that elicits subjective forecast distributions over own-firm future outcomes. In terms of question design, our key innovation lets survey respondents freely select support points and probabilities in five-point distributions. In terms of data collection, our monthly panel Survey of Business Uncertainty covers about 1,750 firms drawn from all 50 states, every major nonfarm industry, and a range of firm sizes. We continue our efforts to expand the panel, improve the quality of SBU data, and better understand how business managers conceptualize uncertainty and form forecasts.

SBU respondents update their forecast distributions frequently, usually by small amounts. When respondents express greater uncertainty today, they make larger future revisions to their forecast distributions. These patterns suggest that respondents are attentive to the survey, and that they supply meaningful data. Indeed, we show that the subjective forecast distributions have predictive power for firm-level sales and employment growth rates in multiple respects: Subjective expectations are predictive of realized growth rates. Subjective uncertainty (the standard deviation of the forecast distribution) is predictive for the magnitude of future forecast errors and the extent of future forecast revisions.

We also develop evidence about the conditions that lead to high subjective uncertainty over own-firm future outcomes. Specifically, subjective uncertainty has a pronounced V-shaped relation to the firm's recent past growth rate *and* to the firm's most recent revision to its expected growth rate. In other words, large recent changes and large recent forecast revisions lead to high forward-looking uncertainty. As the sample grows and firm-level response histories lengthen, the SBU will become increasingly useful for analyzing the determinants of subjective uncertainty and other aspects of belief formation and revision.

Finally, we use the SBU micro data to build monthly indices of aggregate U.S. business expectations and uncertainty for sales growth rates, employment growth rates, and investment rates at a one-year look-ahead horizon. We began publishing these indices in November 2018, and they are now carried by Bloomberg, FRED, and Haver Analytics. We regard these indices as works in progress, but we hope they will aid policymakers and analysts in assessing the outlook for the US economy and the extent of uncertainty about the outlook around events like the COVID-19 pandemic recession.

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Table 1: Summary Statistics for Support Points and Probabilities

	Support Point Outcomes					
Support Point	Employment Growth Rate, Next 12 Months		Sales Growth Rate, Next 4 Quarters		Investment Rate (I/K), 4 Quarters Ahead	
	Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**
1	-0.106	0.166	-0.042	0.123	0.047	0.143
2	-0.049	0.111	0.001	0.087	0.073	0.203
3	0.014	0.080	0.044	0.075	0.110	0.293
4	0.067	0.095	0.081	0.086	0.152	0.390
5	0.115	0.124	0.121	0.111	0.213	0.522
N	7064		7159		6433	

	Support Point Probabilities (%)					
Support Point	Employment Growth Rate, Next 12 Months		Sales Growth Rate, Next 4 Quarters		Investment Rate, 4 Quarters Ahead	
	Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**
1	10.875	9.438	12.438	11.399	12.770	12.310
2	18.318	9.621	18.799	9.346	18.793	9.200
3	41.480	17.801	37.921	15.710	38.340	16.079
4	19.238	11.158	19.933	10.514	19.334	10.586
5	9.459	6.879	10.387	7.119	10.316	7.356
N	7064		7159		6433	

Notes: The upper panel reports means and standard deviations of the five support points in the subjective probability distributions over future own-firm employment growth rates, sales growth rates, and investment rates. The lower panel reports means and standard deviations for the corresponding probabilities. The sample includes all responses between 10/2014 and 10/2019 for which we can construct an expectation.

Table 2: Summary Statistics for Forecast Means, Subjective Uncertainty, and Realizations

Firm-Level Variables	(1) **N**	(2) **mean**	(3) **sd**	(13) **p10**	(14) **p25**	(15) **p50**	(16) **p75**	(17) **p90**
Mean Employment Growth Rate Forecast, Next 12 Months	7,064	0.009	0.080	-0.050	-0.011	0.006	0.033	0.078
Employment Growth Rate Uncertainty, Next 12 Months	7,067	0.058	0.064	0.014	0.022	0.038	0.065	0.117
Realized Employment Growth Rate, Next 12 Months	3,871	0.023	0.162	-0.133	-0.043	0.011	0.082	0.187
Mean Sales Growth Rate Forecast, Next 4 Quarters	7,159	0.041	0.079	-0.016	0.011	0.035	0.067	0.118
Sales Growth Rate Uncertainty, Next 4 Quarters	7,160	0.044	0.048	0.010	0.016	0.028	0.052	0.095
Realized Sales Growth Rate, Next 4 Quarters	3,091	0.050	0.262	-0.250	-0.063	0.047	0.175	0.353
Mean Expected Investment Rate (I/K), 4 Quarters Ahead	6,433	0.115	0.296	0.005	0.013	0.035	0.088	0.240
Uncertainty about Investment Rate (I/K), 4 Quarters Ahead	6,432	0.042	0.105	0.002	0.005	0.013	0.033	0.086
Realized Investment Rate (I/K), 4 Quarters Ahead	7,186	0.091	0.253	0.001	0.008	0.024	0.067	0.180
Current Sales (Millions of Dollars)	7,377	35.738	106.600	0.735	2.625	7.500	21.300	74.450
Current Employment	17,387	401.185	999.226	17.000	58.000	139.000	288.000	700.000
Employment Growth Rate, Past 12 Months (Reported)	7,488	0.021	0.123	-0.095	-0.018	0.017	0.069	0.143

Notes: This table reports summary statistics computed using data from SBU survey waves between 10/2014 and 10/2019. We winsorized the firm-level variables at the 1st and 99th percentiles before computing the summary statistics.

Table 3: What fraction of respondents update their probability distributions for a given outcome between nearest same-topic surveys?

Respondents Revising Their:	**Fraction (SE)**	**N**
Vector of Probabilities for Employment 12 Months Ahead	0.947 (0.005)	4,665
Vector of Probabilities for Sales Growth Next 4 Quarters	0.947 (0.005)	4,786
Vector of Probabilities for Investment 4 Quarters Ahead	0.947 (0.006)	4,639
Vector of Support Points for Employment 12 Months Ahead	0.959 (0.004)	4,665
Vector of Support Points for Sales Growth Next 4 Quarters	0.957 (0.004)	4,786
Vector of Support Points for Investment 4 Quarters Ahead	0.971 (0.004)	4,639
Employment Growth Expectations for Next 12 months	0.998 (0.001)	4,519
Employment Growth Uncertainty for Next 12 months	0.998 (0.001)	4,519
Sales Growth Expectations for Next 4 quarters	0.995 (0.002)	4,757
Sales Growth Uncertainty for Next 4 quarters	0.995 (0.002)	4,757
Investment Rate Expectations for 4 quarters ahead	0.992 (0.002)	4,552
Investment Rate Uncertainty for 4 quarters ahead	0.995 (0.002)	4,552

Notes: The top half of the table reports the fraction of respondents who provide different probabilities or support points between nearest same-topic surveys (i.e., in month t relative to month *t-2* or *t-3) for* each of the three topics covered by the SBU. The bottom half reports the fraction of respondents whose subjective expectations and subjective uncertainty measures change between nearest same-topic surveys. Standard errors in parentheses, clustered by firm. The sample includes all survey waves from 10/2014 to 10/2019.

Table 4: Cosine similarity between responses in nearest same-topic surveys

Vectors of Responses	**Mean Cosine Similarity between vectors reported in months *t* and *t+2* (or *t+3*) (SE)**	**N**
Vector of Probabilities for Employment 12 Months Ahead	0.883 (0.004)	4,661
Vector of Probabilities for Sales Growth Next 4 Quarters	0.884 (0.004)	4,786
Vector of Probabilities for Investment 4 Quarters Ahead	0.878 (0.004)	4,639
Vector of Support Points for Employment Growth 12 Months Ahead	0.844 (0.005)	4,500
Vector of Support Points for Sales Growth Next 4 Quarters	0.885 (0.005)	4,715
Vector of Support Points for Investment 4 Quarters Ahead	0.976 (0.001)	4,634

Notes: This table reports the mean cosine similarity across the response vectors respondents provide in consecutive survey waves, i.e. the cosine between the vector provided in month *t* and the vector provided in month *t+2* or *t+3* when the respondent next receives the survey for the same topic. For each pair of consecutive responses for a given topic, we compute the cosine similarity between the vectors of probabilities and outcomes the respondent provides, and then we compute the mean cosine similarity. Standard errors are in parentheses, clustered by firm. The sample includes all SBU responses between 10/2014 and 10/2019.

Table 5: Autocorrelations of Growth Rate Expectations and Uncertainty

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent Variable	**Sales Growth Expectations, q to q+4**			**Sales Growth Uncertainty, q to q+4**			**log(Sales Growth Uncertainty, q to q+4)**		
Lag Dependent Variable	0.618***	0.623***	0.269**	0.758***	0.778***	0.220***	0.667***	0.665***	0.111***
	(0.084)	(0.083)	(0.128)	(0.065)	(0.073)	(0.047)	(0.030)	(0.032)	(0.022)
Time FE		Y	Y		Y	Y		Y	Y
Firm FE			Y			Y			Y
Observations	4,757	4,757	4,601	4,759	4,759	4,603	4,756	4,756	4,599
R-squared	0.184	0.205	0.403	0.305	0.330	0.487	0.464	0.491	0.686
Firms	752	752	596	752	752	596	752	752	595

Notes: This table estimates the autocorrelations of sales growth expectations and uncertainty looking four quarters ahead, with and without firm and time fixed effects. Data are from the SBU and include all survey waves between 10/2014 and 10/2019. Robust standard errors in parentheses, clustered by firm. *** p<0.01, ** p<0.05, * p<0.1

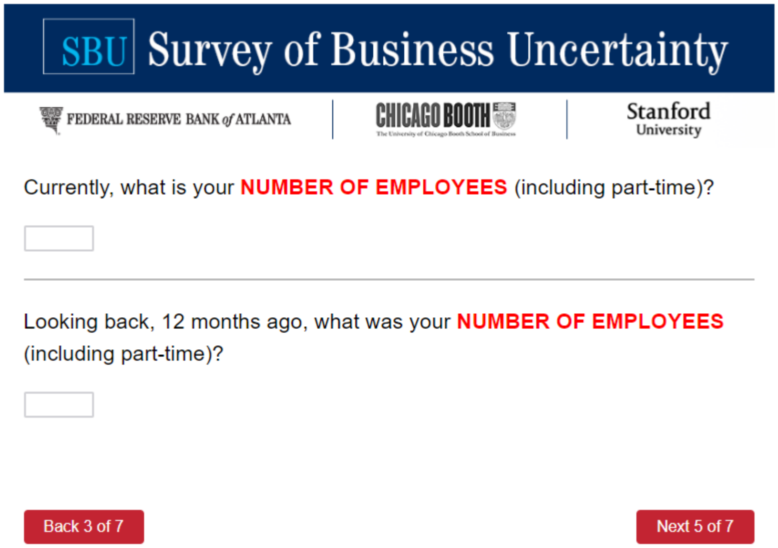
Table 6: Subjective Uncertainty Is Unaffected by the Number of Previous Survey Completions

	(1)	(2)	(3)	(4)	(5)	(6)
	log of Subjective Uncertainty over:					
Dependent Variable	**Sales Growth, Next 4 Quarters**		**Employment Growth, Next 12 Months**		**Investment Rate, 4 Quarters Ahead**	
No. of Previous Responses	-0.004	-0.003	-0.001	-0.005	0.005	-0.015
	(0.004)	(0.005)	(0.003)	(0.004)	(0.009)	(0.012)
Firm FE	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y
Employment-weighted		Y		Y		Y
Mean of Dependent Variable	-3.541	-3.711	-3.245	-3.497	-4.371	-4.474
SD of Dependent Variable	0.880	0.807	0.834	0.773	1.537	1.427
Observations	6,791	6,588	6,712	6,703	6,196	6,042
Within R-squared	3.04E-04	2.22E-04	7.62e-05	7.01E-04	1.85E-04	1.21E-03
R-squared	0.709	0.695	0.796	0.742	0.707	0.681

Notes: We regress the natural logarithm of subjective uncertainty about employment growth over the next 12 months, sales growth over the next four quarters, and the firm's investment rate four quarters hence on the firm's number of previous survey responses using data from SBU survey waves between 10/2014 and 10/2019. Robust standard errors in parentheses, clustered by firm. *** p<0.01, ** p<0.05, * p<0.1

Figure 1: SBU Excerpts, September 2016 Onwards

1a. Employment Questions



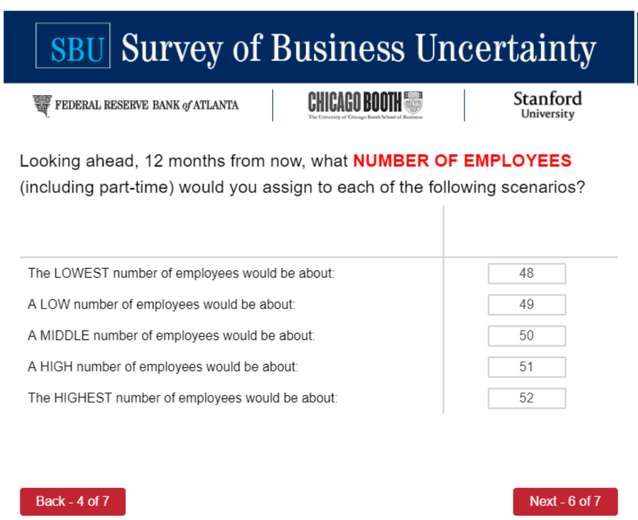
SBU Survey of Business Uncertainty

FEDERAL RESERVE BANK of ATLANTA | CHICAGO BOOTH | Stanford University

Currently, what is your **NUMBER OF EMPLOYEES** (including part-time)?

Looking back, 12 months ago, what was your **NUMBER OF EMPLOYEES** (including part-time)?

Back 3 of 7 | Next 5 of 7



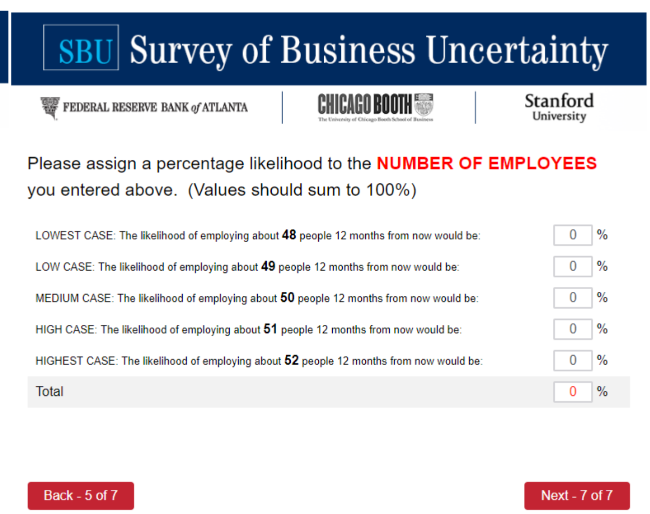
SBU Survey of Business Uncertainty

FEDERAL RESERVE BANK of ATLANTA | CHICAGO BOOTH | Stanford University

Looking ahead, 12 months from now, what **NUMBER OF EMPLOYEES** (including part-time) would you assign to each of the following scenarios?

The LOWEST number of employees would be about:	48
A LOW number of employees would be about:	49
A MIDDLE number of employees would be about:	50
A HIGH number of employees would be about:	51
The HIGHEST number of employees would be about:	52

Back - 4 of 7 | Next - 6 of 7



SBU Survey of Business Uncertainty

FEDERAL RESERVE BANK of ATLANTA | CHICAGO BOOTH | Stanford University

Please assign a percentage likelihood to the **NUMBER OF EMPLOYEES** you entered above. (Values should sum to 100%)

LOWEST CASE: The likelihood of employing about **48** people 12 months from now would be:	0	%
LOW CASE: The likelihood of employing about **49** people 12 months from now would be:	0	%
MEDIUM CASE: The likelihood of employing about **50** people 12 months from now would be:	0	%
HIGH CASE: The likelihood of employing about **51** people 12 months from now would be:	0	%
HIGHEST CASE: The likelihood of employing about **52** people 12 months from now would be:	0	%
Total	0	%

Back - 5 of 7 | Next - 7 of 7

1b. Sales Questions

SBU Survey of Business Uncertainty

FEDERAL RESERVE BANK *of* ATLANTA | CHICAGO BOOTH | Stanford University

For the current quarter, what would you estimate the total dollar value of your **SALES REVENUE** will be?

$ ______

Looking back, over the last 12 months, what was your approximate percentage **SALES REVENUE** GROWTH rate?

____ %

SBU Survey of Business Uncertainty

FEDERAL RESERVE BANK *of* ATLANTA | CHICAGO BOOTH | Stanford University

Looking ahead, from now to four quarters from now, what approximate percentage **SALES REVENUE** growth rate would you assign to each of the following scenarios?

The LOWEST percentage sales revenue growth rate would be about:	-2 %
A LOW percentage sales revenue growth rate would be about:	-1 %
A MIDDLE percentage sales revenue growth rate would be about:	0 %
A HIGH percentage sales revenue growth rate would be about:	1 %
The HIGHEST percentage sales revenue growth rate would be about:	2 %

Back - 1 of 7 Next - 3 of 7

SBU Survey of Business Uncertainty

FEDERAL RESERVE BANK *of* ATLANTA | CHICAGO BOOTH | Stanford University

Please assign a percentage likelihood to the **SALES REVENUE** growth rates you entered. (Values should sum to 100%)

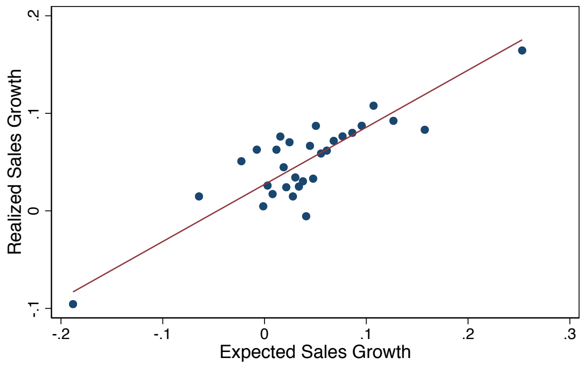
LOWEST: The likelihood of realizing a **-2%** sales revenue growth rate would be:	0 %
LOW: The likelihood of realizing a **-1%** sales revenue growth rate would be:	0 %
MIDDLE: The likelihood of realizing a **0%** sales revenue growth rate would be:	0 %
HIGH: The likelihood of realizing a **1%** sales revenue growth rate would be:	0 %
HIGHEST: The likelihood of realizing a **2%** sales revenue growth rate would be:	0 %
Total	0 %

Back - 2 of 7 Next - 4 of 7

Figure 2: Subjective Sales Growth Rate Expectations Predict Realized Growth Rates

Figure 2a

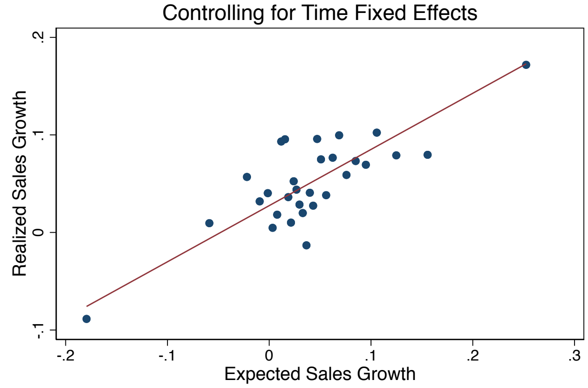
Raw Panel Data



Coeff. = .585, S.E. = .084, R^2 = .026, N = 3037

Figure 2b

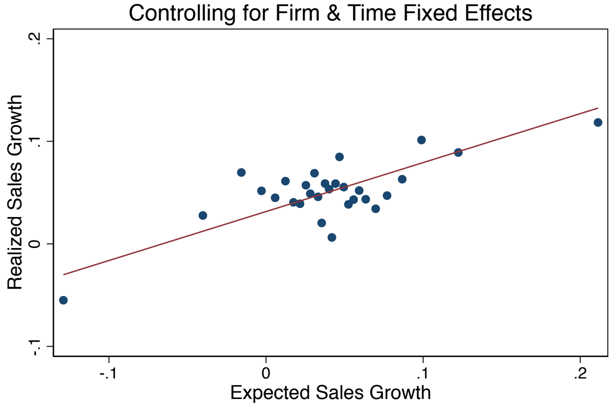
Controlling for Time Fixed Effects



Coeff. = .575, S.E. = .086, Within R^2 = .024, N = 3037

Figure 2c

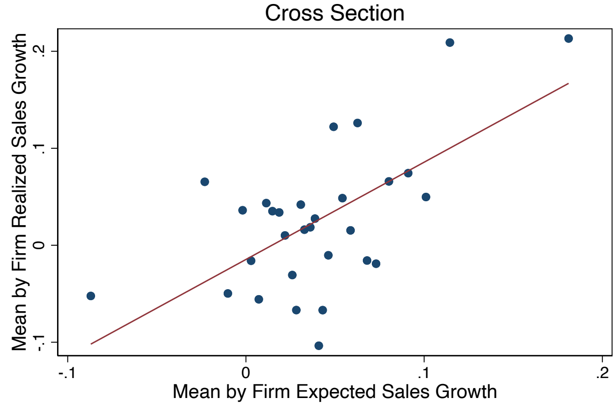
Controlling for Firm & Time Fixed Effects



Coeff. = .477, S.E. = .119, Within R^2 = .015, N = 2913

Figure 2d

Cross Section

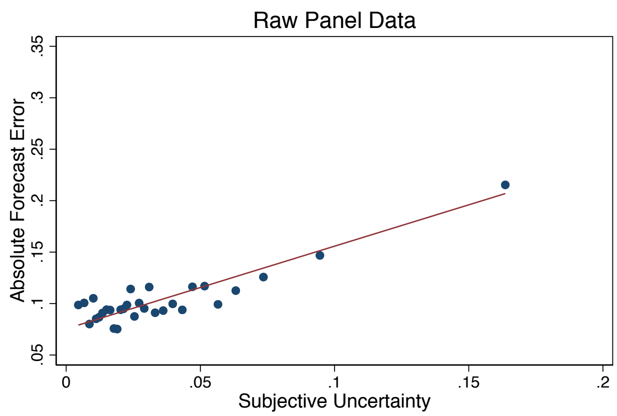


Coeff. = 1.00, S.E. = .229, R^2 = .045, N = 514

Notes: This figure shows bin-scatter plots of sales growth rate expectations for the next 4 quarters on the horizontal axis against realized sales growth rates over the ensuing 4 quarters on the vertical axis. Figure 2a shows the relationship in the raw panel data. Figure 2b controls for time effects. Figure 2c controls for both firm and time fixed effects. Figure 2d shows the relationship in the cross section, showing the mean-by-firm expected sales growth on the horizontal axis and mean-by-firm realized sales growth on the vertical axis. The reported statistics below each figure figure correspond to the OLS regression in the underlying micro data, reporting firm-clustered standard errors. Data are from all waves of the SBU from 10/2014 to 10/2019.

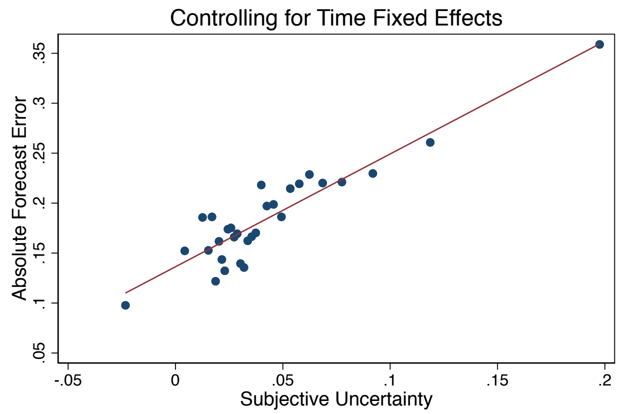
Figure 3: Subjective Uncertainty Predicts Absolute Forecast Errors

Figure 3a



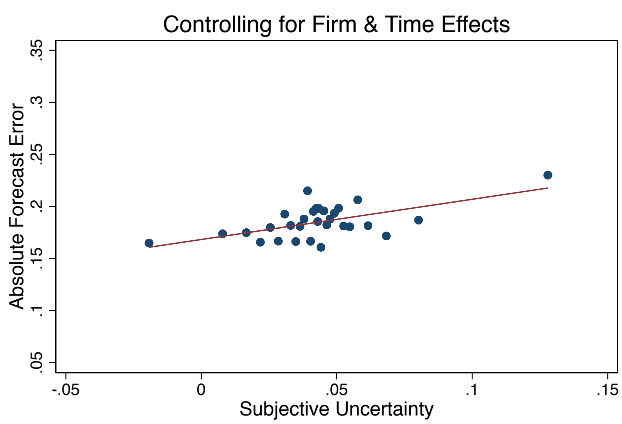
Coeff. = .931, S.E. = .100, R^2 = .048, N = 3037

Figure 3b



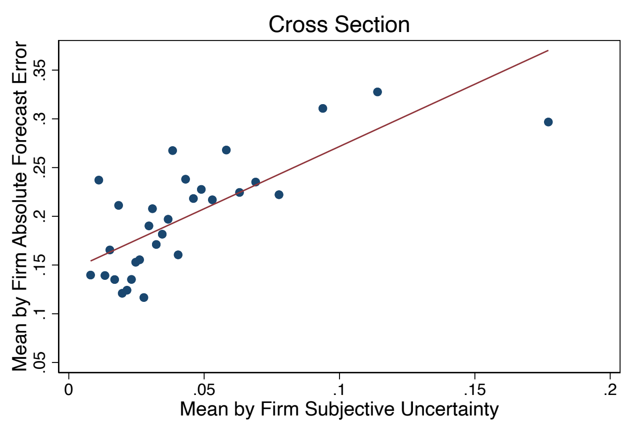
Coeff. = 1.12, S.E. = .108, Within R^2 = .057, N = 3037.

Figure 3c



Coeff. = .386, S.E. = .148, Within R^2 = .004, N = 2913.

Figure 3d



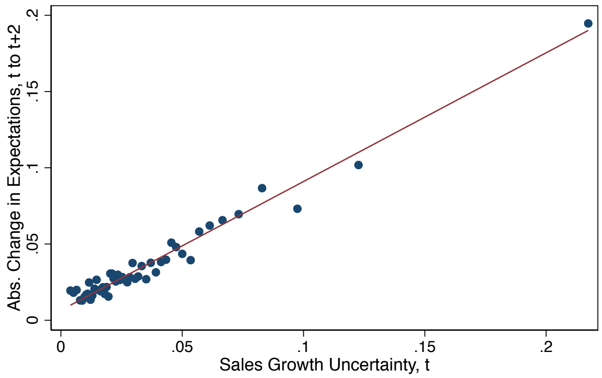
Coeff. = 1.27, S.E. = .239, R^2 = .082, N = 511

Notes: This figure shows bin-scatter plots of subjective uncertainty about the firm's sales growth rate for the next 4 quarters on the horizontal axis, against the respondent's absolute forecast error for its sales growth rate over the ensuing 4 quarters on the vertical axis. Figure 3a shows the relationship in the raw panel data. Figure 3b controls for time effects. Figure 3c also controls for firm effects. Figure 3d shows the relationship in the cross section, plotting mean-by-firm subjective uncertainty on the horizontal axis against the mean-by-firm absolute forecast error on the vertical axis. The statistics below each figure correspond to the OLS regression in the underlying micro data, reporting firm-clustered standard errors. Data are from all waves of the SBU from 10/2014 to 10/2019.

Figure 4: Uncertainty and subsequent expectation revisions

Figure 4a.

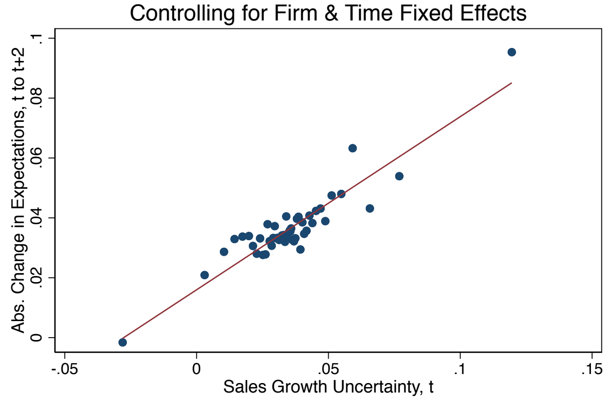
Raw Panel Data



Coeff. = .844, S.E. = .062, R^2 = .287, N = 3961

Figure 4b.

Controlling for Firm & Time Fixed Effects



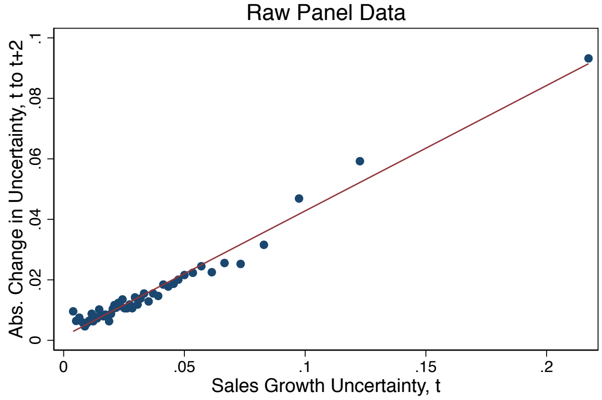
Coeff. = .578, S.E. = .084, Within R^2 = .089, N = 3831

Notes: This figure shows two bin-scatter plots. On the horizontal axis, both show 50 quantiles of subjective uncertainty for sales growth rates over the next four quarters, measured in month *t*. Both have on the vertical axis the absolute value of the change in sales growth rate expectations from months *t* to *t+2* (or *t+3*). On the left, we show the relationship in the raw panel data, while on the right we show the relationship controlling for firm and time fixed effects. We report the underlying firm-level regressions with firm-clustered standard errors at the bottom of each figure, using SBU data from 10/2014 to 10/2019.

Figure 5: Uncertainty and subsequent uncertainty revisions

Figure 5a.

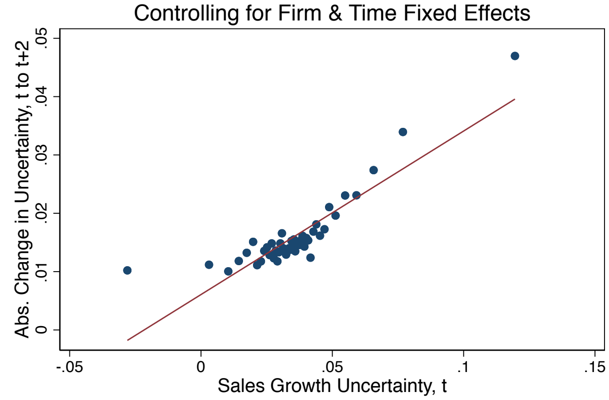
Raw Panel Data



Coeff. = .414, S.E. = .013, R^2 = .446, N = 3961

Figure 5b.

Controlling for Firm & Time Fixed Effects

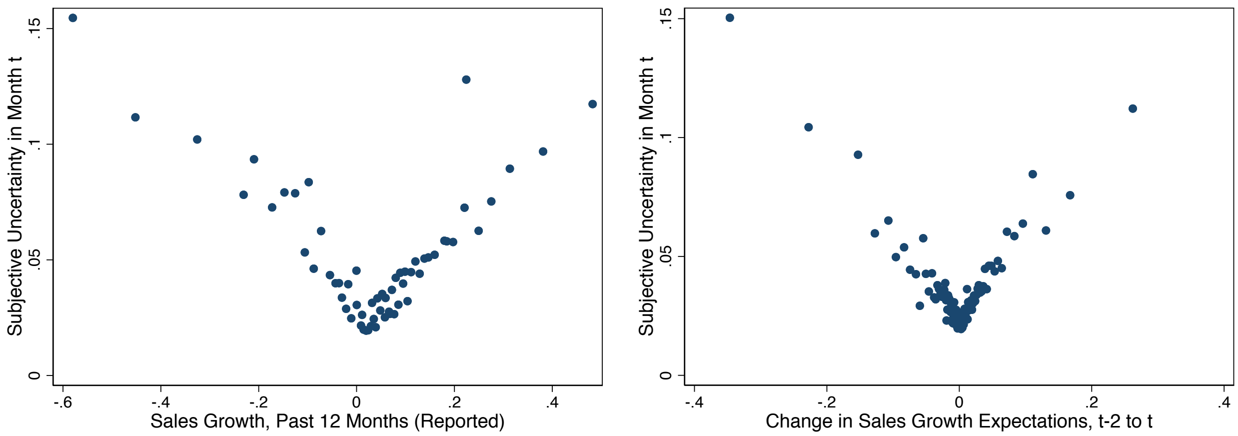


Coeff. = .280, S.E. = .039, Within R^2 = .143, N = 3831

Notes: This figure shows two bin-scatter plots. On the horizontal axis, both show 50 quantiles of subjective uncertainty for sales growth rates over the next four quarters, measured in month *t*. Both have on the vertical axis the absolute value of the change in sales growth rate uncertainty from month *t* to *t+2* (or *t+3*). On the left, we show the relationship in the raw panel data, while on the right we show the relationship controlling for firm and time fixed effects. We report the underlying firm-level regressions with firm-clustered standard errors at the bottom of each figure, using SBU data from 10/2014 to 10/2019.

Figure 6: Subjective uncertainty has a V-shaped relationship to past sales growth and recent forecast revisions

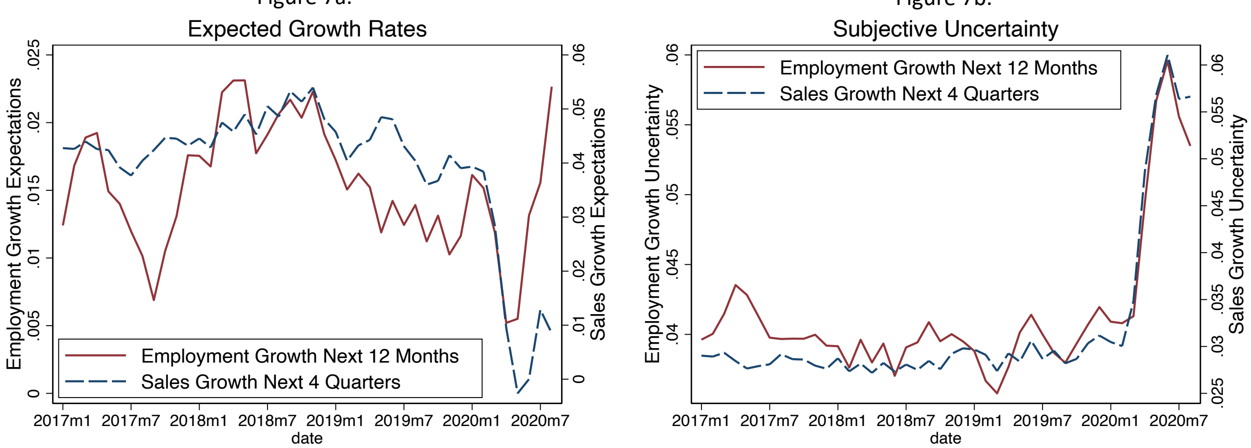
Figure 6a. Figure 6b.



Notes: This figure shows two bin-scatter plots with subjective uncertainty over four-quarter-ahead sales growth rates at *t* on the vertical axis. Figure 6a shows shows 100 quantiles of past sales growth rate from month *t-12* to *t* on the horizontal axis. Figure 6b instead shows 100 quantiles of the change in the four-quarter-ahead sales growth rate expectations from $t-2$ (or t - 3) to t. Data are from the SBU and the sample covers all survey waves from 10/2014 to 10/2019.

Figure 7: Business Growth Rate Expectations and Subjective Uncertainty

Figure 7a. Figure 7b.

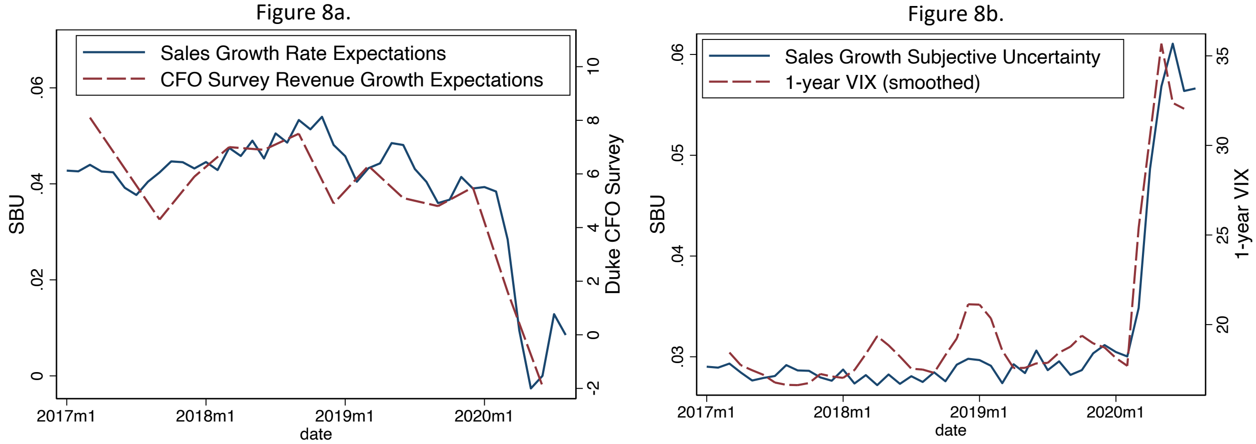


Notes: These figures show average growth rate expectations (left) and average subjective uncertainty about future growth growth rates (right) for employment over the next 12 months and sales over the next 4 quarters.

Figure 8: External comparisons

Figure 8a.

Figure 8b.

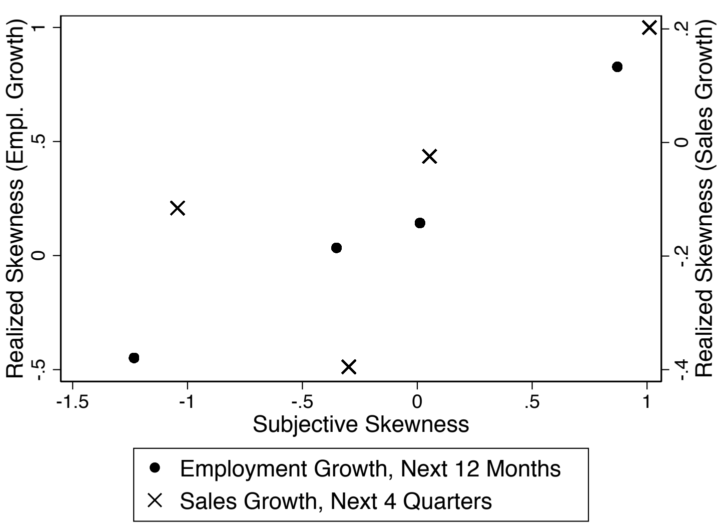


Correlation: .896

Correlation: .953

Notes: The left panel shows our Sales Growth Rate Expectations measure and the revenue-weighted average of the expected change in revenue growth rates for the next 12 months among firms answering the Duke CFO Survey. Because the Duke Survey goes to field in the third month of each quarter, we align its quarterly responses to March, June, September and December. The right panel shows our Sales Growth Rate Uncertainty measure and the 1-year VIX on the 15th day of each month (Source: CBOE via Bloomberg). If the 15th is not a trading day we try the 16th, 14th, 17th, 13th, 18th, or 12th in that order. We smooth the monthly 1-year VIX series using the same procedure as for our Sales Growth Rate Uncertainty measure.

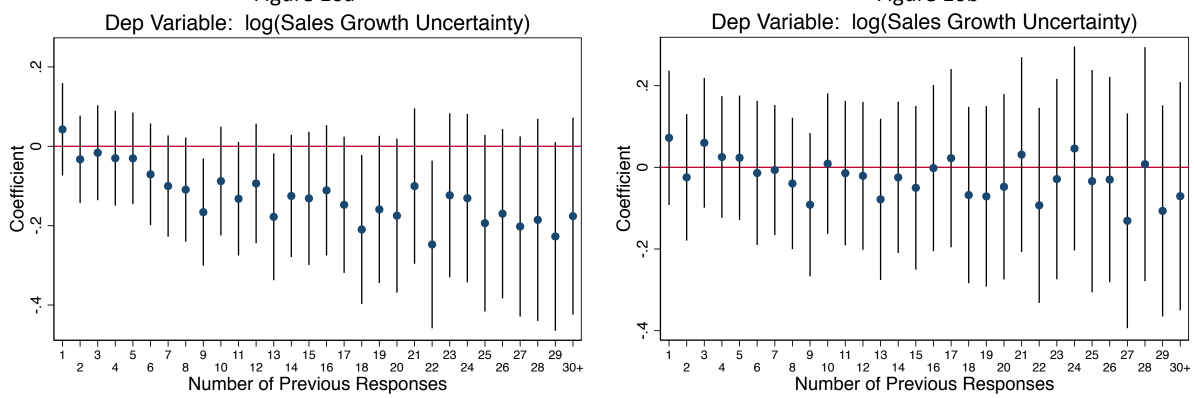
Figure 9: Skewness in realized future growth rates rises with current subjective skewness



Notes: We sort firm-level values for subjective skewness over future sales growth rates into quartiles, and we do the same for subjective skewness over future employment growth rates. For each quartile, we then compute the average subjective skewness values and the skewness of realized employment or sales growth rates over the forecast horizon. The chart displays these quartile-specific values for sales and employment growth rates. N(Employment) = 3,692. N(Sales) = 3,037.

Figure 10: Previous Survey Completions and Subjective Uncertainty

Figure 10a Figure 10b



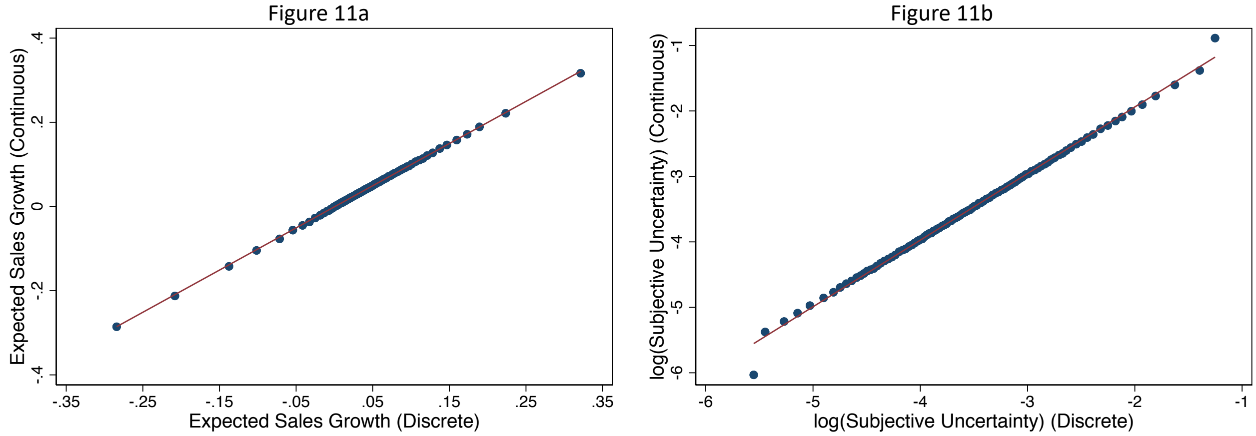
Mean (SD) of Dep. Var: -3.54 (.880)

Mean (SD) of Dep. Var: -3.71 (.806). Employment-weighted

Notes: This figure shows estimated coefficients and 95 percent confidence intervals from regressions of the natural log of sales growth uncertainty (looking ahead over the next 4 quarters) on a set of indicators for the firm's number of previous SBU responses on the right-hand-side as well as firm and time fixed effects (not shown). Figure 4a (left) shows unweighted estimates, while figure 4b (right) weights observations by employment (winsorized at 500 employees). We top-code the number of responses at 30. Data are from the SBU and cover all survey waves between 10/2014 and 10/2019. We construct the 95 percent confidence intervals based on firm-clustered robust standard errors.

Figure 11: Reinterpreting SBU responses as approximations to continuous distributions

Figure 11a Figure 11b



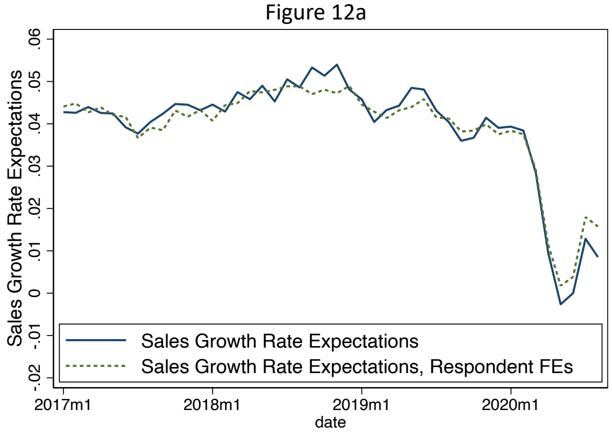
Coeff. = 1.00, S.E. = .001, R^2 = .996, N = 7159

Coeff. = 1.01, S.E. = .006, R^2 = .978, N = 7155

Notes: The figures show bin-scatter plots that compare our measures of subjective mean expectations and uncertainty interpreting SBU responses as discrete or subjective distributions. Our baseline measures interpret SBU responses as discrete, 5-point probability distributions. Alternatively, we can interpret the responses as a continuous distribution consisting of 5 bins, with a uniform distribution within each bin. Figure 12a plots 100 percentiles of our discrete measure of expected sales growth (looking four quarters ahead) on the horizontal axis against the continuous measure of expectations on the vertical axis. Figure 12b repeats the exercise for the natural logarithm of subjective uncertainty. Statistics below the figure correspond to the OLS regression in the underlying microdata, reporting firm-clustered standard errors. Data are from all waves of the SBU from 10/2014 to 10/2019.

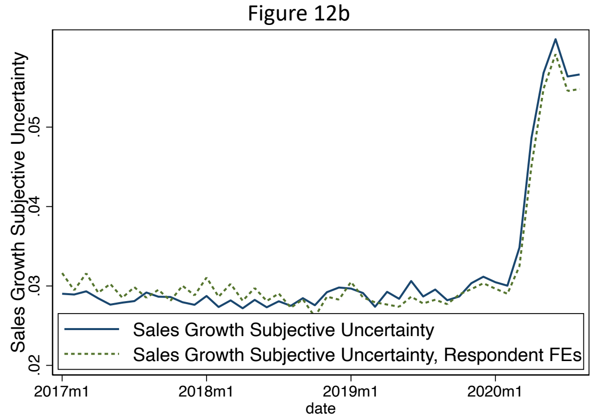
Figure 12: Sales growth rate expectations and subjective uncertainty, with and without controls for panel composition

Figure 12a



Correlation .983

Figure 12b



Correlation .988

Notes: The figures plot our baseline sales growth rate expectations (left) and uncertainty (right) measures alongside alternative measures that account for changing panel composition across months. Our baseline measures are activity-weighted means for expectations or uncertainty in each month. By contrast, the alternative measures compute the same activity-weighted mean with controls for respondent fixed effects. We smooth both measures using the same procedure. Data are from the SBU and cover all months between 1/2015 and 10/2019.