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Abstract: The Census Bureau's 2015 Management and Organizational Practices Survey collected innovative 5-bin data on own future outcomes and probabilities for shipments, employment, capital and materials expenditures at 35,000 manufacturing plants. About 85% of plants provide logically sensible responses to the 5-bin questions, suggesting that most managers can form and express (subjective) probability distributions. The other 15% of plants have lower productivity, employment, wages, managerial education, structured management scores, and multinational ownership. First and second moments of plant-level subjective probability distributions covary strongly with first and second moments, respectively, of historical outcomes, suggesting that our subjective expectations data are well founded. Finally, our plant-level subjective uncertainty measures correlate positively with realized stock-return volatility, option-implied volatility and analyst disagreement about future earnings for the plant's parent firm and for the median publicly listed firm in the plant's industry.

Keywords: Subjective expectations, business-level uncertainty

JEL Classification: L2, M2, O32, O33.

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1 Introduction

Keen interest in expectations harkens back at least to Keynes, who stressed the importance of "animal spirits" for firms and the macroeconomy. Classic contributions by Hayashi (1982) and Abel and Blanchard (1986) highlight the payoff to modelling business expectations in dynamic models of investment. Indeed, virtually all modern studies of investment, hiring and R&D under adjustment costs recognize the importance of expectations in business decision making. Leading examples include Nickell (1978), Caballero (1997), Chirinko (1993) and Dixit and Pindyck (1994). Despite their importance, however, we have few direct measures of business-level expectations for real variables beyond qualitative indicators and point forecasts.[1]

This paper describes the first results of an ambitious survey of business expectations conducted in partnership with the U.S. Census Bureau as part of the Management and Organizational Practices Survey (MOPS).[2] MOPS is the first-ever mandatory government management survey, covering more than 30,000 plants across more than 10,000 firms. Thus far, it was run in two waves, 2010 and 2015.[3] The size and high response rate of the dataset, its coverage of units within a firm, links to other Census data, and comprehensive coverage of manufacturing industries and regions make it unique. As part of the 2015 MOPS, we asked 8 questions regarding plant-level expectations of own current-year and future outcomes for shipments, employment, investment expenditures and expenditures on materials. The survey questions elicit point estimates for current-year (2016) outcomes and five-point probability distributions over 2017 (next-year) outcomes, yielding a much richer and more detailed dataset on business-level expectations than previous work, and for a much larger sample.

Among plants in the 2015 MOPS publication sample, we find that 85% provide logically sensible responses to our 5-bin questions, suggesting that most managers can form and express detailed subjective probability distributions. The other 15% of plants have lower productivity, employment, wages, managerial education, structured management scores, and multinational

1 Guiso and Parigi (1999) and Bontempi, Golinelli and Parigi (2010) use 3-point probability distributions from a survey of about 1,000 Italian firms per year from 1994 to 2006, and Masayuki (2013) uses 2-point distributions from a survey of 294 Japanese firms in 2013. See Bachman, Elstner and Sims (2013) and Manski (2017) for additional discussion and references to previous efforts to measure business and household expectations.

2 This survey was made possible by the generous provision of over $1million in research support from our primary sponsors – the U.S. National Science Foundation, the Kauffman Foundation and the Sloan Foundation.

3 See the descriptions of MOPS in Bloom, Brynjolfsson, Foster, Jarmin, Saporta-Eksten, and Van Reenen (2013) and Buffington, Foster, Jarmin and Ohlmacher (2016).

ownership. First and second moments of plant-level subjective probability distributions covary strongly with first and second moments, respectively, of historical outcomes, suggesting that our subjective expectations data are well founded. Finally, our plant-level subjective uncertainty measures correlate positively with realized stock-return volatility, option-implied volatility and analyst disagreement about future earnings per share for the plant's parent firm and for the median publicly listed firm in the plant's industry.

The paper proceeds as follows. Section 2 discusses the MOPS sample and measurement of plant-level expectations. Section 3 reports common shapes for the subjective probability distributions, assesses whether respondents express sensible probability distributions, and investigates how the ability to express a sensible distribution relates to plant size and age, plant performance, and the quality of its management practices. Section 4 examines how moments derived from the subjective expectations data vary with past growth and volatility at the plant level and with widely used proxies for firm-level uncertainty and volatility. Section 5 concludes.

2 Measuring Business Expectations

The first wave of the Management and Organizational Practices Survey (MOPS) went to field in 2011 as a mandatory supplement to the 2010 Annual Survey of Manufacturers (ASM).[4] This plant-level survey contained a range of questions about management and organizational practices plus some background characteristics (but nothing on expectations). The success of this survey led to a second MOPS wave as a supplement to the 2015 ASM, which added two new sections, Section C on "Data and Decision-Making" and Section D on "Uncertainty," and expanded Section E on "Background Characteristics." Section D contained 8 questions on plants' expectations for 2016 and 2017 over four outcomes: shipments, investment expenditures, employment and materials expenditures. The MOPS contains a question for "Certification," where the respondent designates the "name of [a] person to contact regarding this report" as well as that person's title. Based on this certification data, the 2015 MOPS survey was typically answered by senior plant management, in that the most common position of the contact name is "plant manager" (15%), "financial controller" (10%) or "president/CEO" (8%), with almost 90% within broad categories of

4 For more details see Buffington, Foster, Jarmin and Ohlmacher (2016). Note that the ASM is a retrospective survey, so the April 2011 survey wave asked about data for calendar year 2010.

"management" or "finance" (see Table A1).

The question for 2016 elicited a point estimate, asking (for example for shipments) "*For calendar years 2015 and 2016 what are the approximate values of products shipped, including interplant transfers, exports and other receipts at this establishment? Exclude freight and exercise taxes?*"[5] Since the survey was sent out in April 2016 with collection ending in October 2016, the 2015 figure would have likely been known, and was requested to provide a benchmark for growth rates. The 2016 figure, however, would have been a partial-year forecast.

The corresponding question for 2017 asked for the lowest, low, medium, high and highest possible outcomes for shipments, as well as and the corresponding probabilities such that they add to 100%. Since this question is more complex, the survey questionnaire included a vignette (pre-completed example) to help explain the question. See Figure 1 for the vignette.[6] The idea behind this question is to collect probability distributions over own-plant outcomes. The 5-bin outcome and probability structure offers a feasible level of response detail based on pre-testing of the survey in multiple rounds of cognitive testing with the Census Bureau and the Federal Reserve Bank of Atlanta from 2013 to 2015. [7] It is also extremely flexible in that respondees have 9 degrees of freedom to characterize their expectations – 5 outcomes and 5 probabilities less one restriction that the probabilities add to 100%.

There are good reasons for this two-part structure: asking first for outcomes distributed over 5 bins, and then asking for the associated probabilities. Pre-defined outcomes bins, as in the Survey of Professional Forecasters[8] for macro outcomes, do not yield adequate spread and granularity across thousands of plants that vary greatly by age, size and industry unless we use many, many more bins. Because annual GDP growth rates for the United Sates are highly likely to fall within the -3% to +4% range, eight outcome bins can adequately span the relevant range of possibilities with reasonable granularity. For individual manufacturing plants, however, annual

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[5] The language describing the response variables for all eight questions in Section D is identical to the corresponding questions on the ASM. Definitions of these variables identical to the definitions provided in the ASM instructions were also provided on a FAQ webpage. https://www.census.gov/programs-surveys/mops/about/faq.html

[6] We test for anchoring effects in section 3 below and find 5% or less of respondents provide vignette probabilities to questions and very few individuals (too few to disclose) provide vignette outcomes.

[7] Bloom and Davis worked with a team at the Atlanta Fed to develop a similar survey on a smaller panel of around 1,000 firms to collect monthly expectations data over time, and to provide first and second moment aggregate indicators to help inform monetary policy. For information on the cognitive testing process for the MOPS, see Buffington, Herrell, and Ohlmacher (2016).

[8] See https://www.philadelphiafed.org/research-and-data/real-time-center/survey-of-professional-forecasters/.

growth rates range typically have far larger ranges (for example, from -50 to 100 percent or more) and the central tendency of likely outcomes differs greatly over plants. To encompass a range from -50 to 100% with one-point spreads between nodes would require 151 bins. In addition to the practical consideration, we also wanted to avoid anchoring or tilting the responses by pre-specifying the support of the subjective probability distributions. Hence, we instead designed a survey that first let businesses define their own outcome bins and then assign probabilities to these bins. Moreover, the great flexibility of the design with 5 outcomes and 5 probabilities meant complex expectational distributions could be captured, avoiding limiting respondees to, for example, normal or triangular probability distributions.

This survey was sent electronically as well as by mail to the physical address of each establishment, with response mandated by Federal law. Most respondents (80%) completed the survey electronically, with the remainder completing the survey by paper. Non-respondents were mailed a follow-up letter after six weeks. A second follow-up letter was mailed if no response had been received after 12 weeks. The first follow-up letter included a copy of the MOPS instrument.

2.1 Sample and Sample Selection

The sampling frame for the 2015 MOPS was the sampling frame for the 2015 ASM. All plants in the mail sample for the 2015 ASM as of January 2, 2016 were mailed a copy of the MOPS survey instrument and instructions for reporting on April 28, 2016. As noted above, two follow-up letters were sent to potential respondents on an as-needed basis. Collection of responses closed on October 31, 2016. The MOPS sample was also supplemented in the first follow-up mailing with new plants of multi-unit firms and newly in-scope manufacturing plants identified from ASM responses.

Of the approximately 50,000 plants in the MOPS mail sample, about 35,000 establishments returned responses that were considered valid for inclusion in officially published tables by the U.S. Census Bureau. In order to be included in this tabulation sample, respondents needed to provide answers to all seven questions in Section A (questions 1, 2, 6, and 13-16) that could not be skipped according to the instructions in the survey. The official Unit Response Rate (URR) computed by the U.S. Census Bureau is the number of respondents divided by the number of respondents who were either eligible for response or for whom eligibility could not be determined. That is, the denominator of the URR also includes plants whose forms were returned to the Census Bureau by the U.S. Postal Service as "Undeliverable as Addressed." The URR for the 2015 MOPS was 70.9%, compared to 74% for the 2015 ASM. These MOPS respondents accounted for 71.9% of 2015 ASM shipments reported by all plants in the MOPS sample.

The MOPS follows a relatively unique mail strategy for a Census Bureau survey. For the ASM (and many other surveys), the Census Bureau mails survey forms and instructions to the "business address" associated with plants in the Business Register (BR). In general, for plants belonging to multi-unit firms, this means that survey forms are mailed to a central address (often headquarters). In contrast, the MOPS is mailed directly to the physical address of the plant.[9] This mail strategy is pursued because managers at the physical plant are more likely to have information about plant-level management practices. Where a contact name for the plant was available in the BR, the form and instructions for the MOPS were addressed to that name. Otherwise, these packages were mailed attention: "Plant Manager." For more technical information on the MOPS sample and collection and processing, see Buffington, Hennessy, and Ohlmacher (2017) or https://www.census.gov/programs-surveys/mops/technical-documentation/methodology.html.

The baseline sample for our analysis is the set of 35,000 respondents[10] to the 2015 MOPS who could be matched to 2015 ASM results and were thus included in the published MOPS tables. Further sample restrictions are assigned as discussed below according to the availability of valid responses to the forecasting questions. The forecasting data underwent a rigorous cleaning process that is detailed in the data appendix.

3 Response Characteristics

Table 1 reports the 10 most common subjective probability distributions elicited by the question on future shipments. About 7% of all respondents fail to answer the 5-bin questions about

[9] If a mailing to the physical address of a plant belonging to a multi-unit firm was returned as UAA, subsequent follow-up mailings were sent to the business address associated with that plant.

[10] For clearance purposes sample sizes have been approximated.

future shipments, which we interpret as inability or unwillingness to express subjective probability distributions.[11] Rows (2) to (10) report the next 9 most common probability distributions. The vignette is the 4th most common distribution, accounting for 5% of respondents, which suggests a mild degree of anchoring. By way of comparison, only 2% of respondents report the mirror image of the vignette, with 20% of the mass in the Low bin and 10% in the High bin. As seen in Row 5, about 4% of respondents report a uniform probability distribution for future shipments.

Table 2 considers quality indicators for the subjective expectation responses to the questions about future shipments. It also considers how response quality and other characteristics of the subjective distributions vary with selected plant characteristics. We regard three conditions as minimal requirements for a "good response" to our questions about subjective expectations. First, 90% of plants report probabilities that sum to a value between 95 and 105%.[12] Second, 97% report a distribution with at least two mass points. Third, 85% report future shipments that rise in a weakly monotonic manner over the five bins from Lowest to Highest. Perhaps surprisingly, 85% of respondents express subjective probability distributions over future shipments that meet all three requirements for a "good response." Similar results hold for questions about subjective expectations over employment, capital and materials expenses. This pattern of results says that management at most plants can form and express coherent probability distributions in response to our 5-bin questions. We think this pattern suggests that our subjective expectations data will provide useful inputs into dynamic models whereby current business decisions depend partly on expectations about future outcomes, as in models that involve Bellman equations.

Turning to Columns (2) to (6) in Table 2, we see that an ability to express "good" subjective probability distributions is associated with higher management quality scores as measured by Bloom et al. (2013). Apparently, plants that adopt more structured management practices around monitoring performance and incentives also have managers that are more able to provide coherent probability distributions. Good responses are also associated with greater size as measured by employment, higher earnings per worker, a larger fraction of managers with a college education and a higher incidence of multinational ownership. The same pattern holds for each of the

[11] Those leaving these responses blank did typically complete prior and subsequent questions (and were required to have provided sufficient responses to Section A for inclusion in the sample), so they are not simply skipping the entire survey.

[12] If respondents round at the cell level, their reported probabilities need not sum to exactly 100%. In practice, very few respondents supply probabilities that lie within 95% to 105% but do not sum to exactly 100%.

individual response quality indicators as well, confirming our interpretation of the response quality indicators. These results also prompt the hypothesis that an ability to form and express coherent subjective probability distributions leads to better plant-level outcomes.

The last four rows consider other aspects of the subjective probability distributions and their empirical relationship to the plant characteristics. Subjective probability distributions characterized by an interior mode are associated with better management practices, greater employment, higher earnings per worker, and greater managerial education. Results are similar for subjective distributions with a single mode and, in attenuated form, for symmetric distributions. These results suggest that better performing plants are more likely to provide the "regular" sorts of distributions that we usually see in actual outcomes for plants, firms and industries.

In summary, Tables 1 and 2 demonstrate that, firstly, a surprisingly large number of plants can provide well-formed 5-bin outcome 5-bin probability distributions, suggesting more complex models of economics behavior involving the formation of expectations across future states are not implausible for plants. Second, those plants that are unable to provide these probability distributions are not randomly selected. Instead, they appear to be significantly worse on several performance metrics.

4 Response Quality

In this section we validate the quality of the expectations data by showing that our measures of subjective uncertainty are highly correlated with observables that one would expect to be indicative of plant expectations. The first test we run is to regress the first moment of plant expectations of the growth in shipments, investment, employment, and materials expenditures on realized growth rates in the prior year. Results of this test are presented in Table 3. Column (1) shows that a plant's expected growth in shipments from 2015 (using reported shipments from the 2015 MOPS) to 2017 is extremely correlated (significant at the 1% confidence level) with its shipments growth rate from 2014 to 2015 (using reported sales from the 2014 and 2015 ASM). Conversely, column (2) shows that expected investment growth from 2015 to 2017 is highly *negatively* correlated with investment growth between 2014 and 2015. This is likely due to plants making lumpy capital investments such that those which made capital investments in the previous year are less likely to do so in the immediate future (see Cooper and Haltiwanger, 2006).

Employment and materials growth expectations are similar to shipments growth expectations - expected employment growth is positively correlated with past employment growth (column 3), and expected materials expenditures growth (column 4) is positively correlated with past growth in materials expenditures. Columns (5) through (8) regress expected growth measures on all four realized prior-year growth rates simultaneously. Prior shipments, investment, and employment growth are each strong predictors of plant mean expectations, while prior materials expenditures growth does not appear predictive of expectations conditional on the other realized growth measures, likely due to a high degree of correlation between materials cost and shipments. We also looked at longer run measures of growth – for example, shipments growth from 2012-to 2015 – and found very similar results.

Table 4 conducts a similar analysis for the second moment of plant expectations. We construct measures of plant historic shipments (investment, employment, materials) growth volatility by taking the log standard deviation of every realization of annual plant growth in shipments (investment, employment, materials) from 2004 through 2015, as available. Only plants with at least 5 observations on historic growth rates are kept, somewhat shrinking the sample size.[13] Columns (1) through (4) show that a plant's historic realized volatility is highly positively correlated with subjective uncertainty over future growth rates (log standard deviation in the growth rates forecast for 2017). This is also shown for shipments in Figure 2, where we see an extremely strong and almost completely linear upwards sloping relationship between historic shipments volatility and subjective shipments uncertainty. This is a striking result – plants subjective uncertainty over future sales growth is extremely tightly related to its historic volatility of sales growth, indicating the second-moment variations in these expectations is informative.

In Table 4 columns (5) through (8) we include all of the historic volatility measures simultaneously. For example, column (5) regresses shipments growth uncertainty on realized shipments, investment, employment, and materials growth volatility. Each of the measures is a strong predictor of subjective uncertainty. However, comparing the t-statistics for each independent variable it is clear that past shipments growth volatility is the most significant

[13] This inclusion criteria means that plants have to be included in at least two prior ASM survey waves. Given larger plants have a higher probability of being included in each ASM survey wave, this will oversample larger plants.

predictor of future shipments growth uncertainty. The same is true for the other outcomes we measure – in columns (6) through (8) the most significant predictor of uncertainty with respect to each outcome is past volatility of that outcome. This pattern highlights how plant-level subjective uncertainty varies across outcomes in line with their historic experiences – for example, plants with historically highly volatile shipments but stable employment report relatively greater subjective uncertainty for shipments as compared to employment.

This fact that uncertainty over each outcome is most correlated with that outcome's past volatility suggests that there is a great deal of informational content in the subjective expectations data. In particular, it suggests that there is independent information about plant subjective uncertainty in each of the solicited expectations distributions. In Table A2, we provide further evidence of this by showing the pairwise correlations of the first (second and third) moments of the expectations distributions for each outcome variable. While the moments of the distributions are correlated with one another, the correlation is by no means close to one – for example the second moment of shipments and materials cost have the highest correlation of 0.55 compared to a correlation of 0.24 between the second moments of shipments and investment – so there is quite a bit of independent variation in the expectations over each outcome.

In the final column of Table 4, we add measures of firm and industry realized volatility to the regression of shipments growth uncertainty on plant realized volatility. Conditional on the plant's own history of shipments growth volatility, historic volatility of other plants in the same firm and of other plants in the same industry are both strongly positively correlated with plant subjective uncertainty. In unreported regressions we show that results for uncertainty over investment, employment, and materials growth are similar.

Summarizing the results in Tables 3 and 4, the expectations data provided by MOPS plants is strongly correlated with historical realizations. Faster growing plants report higher mean expected future growth rates and plants with more volatile histories report more disperse expected future growth rates. This is an important validation of the quality of the expectations data. The fact that expectations are strongly correlated to observables which a priori seem likely to influence expectations suggests that the information provided is high quality in the sense that plants are taking the survey seriously and providing thoughtful responses to the expectations questions.

In Table 5 we show that the proxies for firm uncertainty commonly used in the literature are strongly correlated with our subjective uncertainty data, providing an empirical justification for the widespread use of these measures. The three firm-specific proxies for uncertainty which we consider are (a) realized stock returns volatility, (b) options-implied volatility, and (c) forecaster disagreement. For this analysis, we match the Census data to stock market data on publicly-listed firms, which reduces the sample from about 26,000 to 5,000 plants.

In column (1) of Table 5 we regress plant subjective shipments growth uncertainty on the log standard deviation of daily stock returns of the plant's parent firm over the prior year. Daily stock returns are a common measure of firm uncertainty, used by dozens of papers, for example Leahy and Whited (1996) and Bloom, Bond and Van Reenen (2007). We find there is a strong positive relationship between the two - a 10% increase in realized firm stock market volatility is associated with a 1.17% increase in plant subjective uncertainty. The relationship between subjective uncertainty and stock market volatility remains when we include industry fixed effects and controls for plant size, age, management practices, and plant manager skills in column (2). In column (3) we conduct the analysis at the industry-level by regressing plant uncertainty on the log standard deviation of daily stock returns for the median firm within the same industry as the plant. Since this specification does not require us to match to firm-specific data on publicly-listed firms, the sample in column (3) is the full sample of plants which had good expectations data for all four outcomes. Even at this more aggregate level, there is a strong relationship between industry-specific stock market volatility and subjective uncertainty (significant at 1% level). This suggests industry level stock-volatility can provide a good proxy for the uncertainty in both public and private firms in the same industry.

In Columns (4) through (6) we consider options-implied volatility of the parent firm's stock as a proxy for firm uncertainty, which is a common measure in a range of papers including, for example, Paddock, Siegel and Smith (1988), Bloom (2009) and Kellogg (2014). Specifically, we regress plant uncertainty on average 91-day options-implied volatility of the plant's parent firm in the year preceding the survey using data from Option Metrics. The results are similar to those using realized stock market volatility, with a 10% increase in implied volatility associated with a 2.12% increase in plant subjective uncertainty in column (4) and a 1.2% increase after including industry fixed-effects and plant controls in column (5). In column (6) we generate the industry average measure of implied volatility across all firms in Option Metrics and regress the average across all 26,000 plants against this, again finding a highly significant positive relationship. This suggests implied volatility – which is probably the most commonly used measure of firm-uncertainty[14] – is highly correlated with survey measured subjective uncertainty.

Finally, columns (7) through (9) show the relationship between subjective uncertainty and forecaster disagreement. Forecaster disagreement, while having an ambiguous theoretical relationship with uncertainty, has a long history of as a strong empirical indicator of uncertainty (see, for example, Bachman, Elstner and Sims 2013). We examine the relationship between earnings forecast disagreement – measured as the log coefficient of variation of analyst forecasts of earnings per share in fiscal year 2017 using Institutional Brokers' Estimate System (IBES) data – and subjective uncertainty. Disagreement on firm-level earnings using IBES data has been used by a range of papers as a proxy for uncertainty, including, for example, Bond and Cummins (2004) and Xiao (2016). We find that forecast disagreement is highly correlated with subjective uncertainty at the firm-level in columns (7) and (8) with and without a set of industry and firm controls, and on average across industries in column (9).

5 Conclusion

The 2015 MOPS fielded in partnership with the U.S. Census Bureau included innovative questions asking plants to provide five-bin outcome and probability forecasts over future shipments, employment, capital expenditures and expenditures on materials. Preliminary analysis of responses from approximately 35,000 manufacturing plants shows that approximately 85% of respondents could provide multi-point forecasts meeting a set of inclusion criteria, signaling an ability by managers to answer forecasting questions of this kind. Plants for which valid forecasts were not provided exhibit less structured management practices, have fewer employees, are less productive, have less educated managers, and less frequently belong to multinational firms. Furthermore, the first two moments of the distributions of these forecasts are strongly correlated with historic moments of the variables in question. Finally, the measures of subjective uncertainty computed from this new dataset are significantly correlated with commonly-used proxies for business uncertainty such as stock market volatility, options-implied volatility, and forecaster disagreement.

[14] See, for example, the survey of measures of uncertainty in Bloom (2014).

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Appendix

Data cleaning procedure

Forecasting data for 2017 underwent a detailed cleaning process. The cleaning rules included both flagging categories of responses and, in some cases, editing responses based on those flags. The editing and imputation rules for these questions are as follows:

1. Create a variable counting the number of missing outcomes (ranges from 0 to 5) and probabilities (ranges from 0 to 5)
2. Flag response patterns that are "1, 2, 3, 4, 5" and 2016 point estimate suggests this was simply numbering the response options
3. Flag response patterns that are the same as the example from the survey instrument
4. Impute missing probabilities with zero
5. Divide probability by 10 if doing so makes the sum of the five probabilities equal to 100
6. Multiply probabilities by 100 if they sum to one
7. Impute missing values for outcomes with associated probabilities equal to zero
8. Flag responses with probabilities that sum to 100
9. Flag responses with probabilities that sum to between 90 and 110 (inclusive). These are then rescaled so that they sum to 100
10. If the response pattern for outcomes is not weakly increasing, but adding either one or three zeroes to **one** of the responses would make the outcomes weakly increasing, then impute the value that would make the outcomes weakly increasing. If changing more than one response in this manner would make the outcomes weakly increasing, no change is made.
11. If the response pattern for outcomes is not weakly increasing, but dividing **one** of the responses by 10 or 1000 and truncating the decimal would make the outcomes weakly increasing, then impute the value that would make the outcomes weakly increasing. If changing more than one response in this manner would make the outcomes weakly increasing, no change is made.
12. If the response pattern for outcomes is weakly decreasing, reverse the order of responses and associated probabilities.
13. Create indicator variables for each of the following
    a. Outcome distribution is weakly/strictly increasing
    b. Probability distribution is symmetric
    c. Probability distribution is unimodal
    d. Probability distribution is bimodal
    e. Probability distribution has an interior mode (i.e. low, medium, or high scenario is most likely)
    f. Probability distribution has a centered mode (i.e. medium scenario is most likely)

g. Outcomes are not all identical

h. Probability distribution does not have 100% assigned to any outcome

14. Create an indicator variable for "good" responses. The indicator is equal to one if all of the following hold:

a. Outcome distribution is weakly increasing

b. More than one scenario is reported

c. Probability distribution does not have 100% assigned to any outcome

d. Probabilities sum to between 90 and 110 (inclusive)

e. Responses are not "1, 2, 3, 4, 5" and the respondent's 2016 estimate suggests this was not simply numbering the response options

15. Trim top and bottom values using the following procedures:

a. If $|\text{highest} - \text{high}| > \alpha^*|\text{high} - \text{medium}|$ and $|\text{highest} - \text{high}| \leq \beta^*|\text{high} - \text{medium}|$, for each of other three questions, then impute highest = high + $|\text{high} - \text{medium}|$.

b. If $|\text{lowest} - \text{low}| > \alpha^*|\text{low} - \text{medium}|$ and $|\text{lowest} - \text{low}| \leq \beta^*|\text{low} - \text{medium}|$, for each of other three questions, then impute lowest = low - $|\text{low} - \text{medium}|$

16. For all respondents who have data in all ASM survey waves from 2004-2015, responses are manually reviewed and any typos are corrected.

Editing is less common in responses received electronically because the online form provides built-in calculation functions and edits that identify potential reporting issues. The former calculated the sum of probabilities provided by the respondent, making it easier for respondents to ensure that probabilities summed to 100%. Respondents received error messages (that could be ignored) if response values were not weakly increasing, any cell was left empty, or probabilities did not sum to 100%. Furthermore, probabilities less than zero or greater than 100 could not be entered in the online form.

Figure 1: The Expectations Vignette from the MOPS 2015 survey

Section D - Uncertainty

The following examples illustrate how a plant could complete the type of questions asked in this section. All examples are fictional. If your forecasts do not include the level of detail requested or do not exist, please report according to your best judgment. ***Estimates are acceptable.***

Example A: Jane Doe is filling out this survey for Plant A. In 2015, Plant A had approximately $4,500,000 in products shipped, with a forecast of $4,750,000 in 2016.

For calendar years 2015 and 2016, what are the approximate dollar values of **products shipped**, including interplant transfers, exports and other receipts at this establishment? Exclude freight charges and excise taxes.

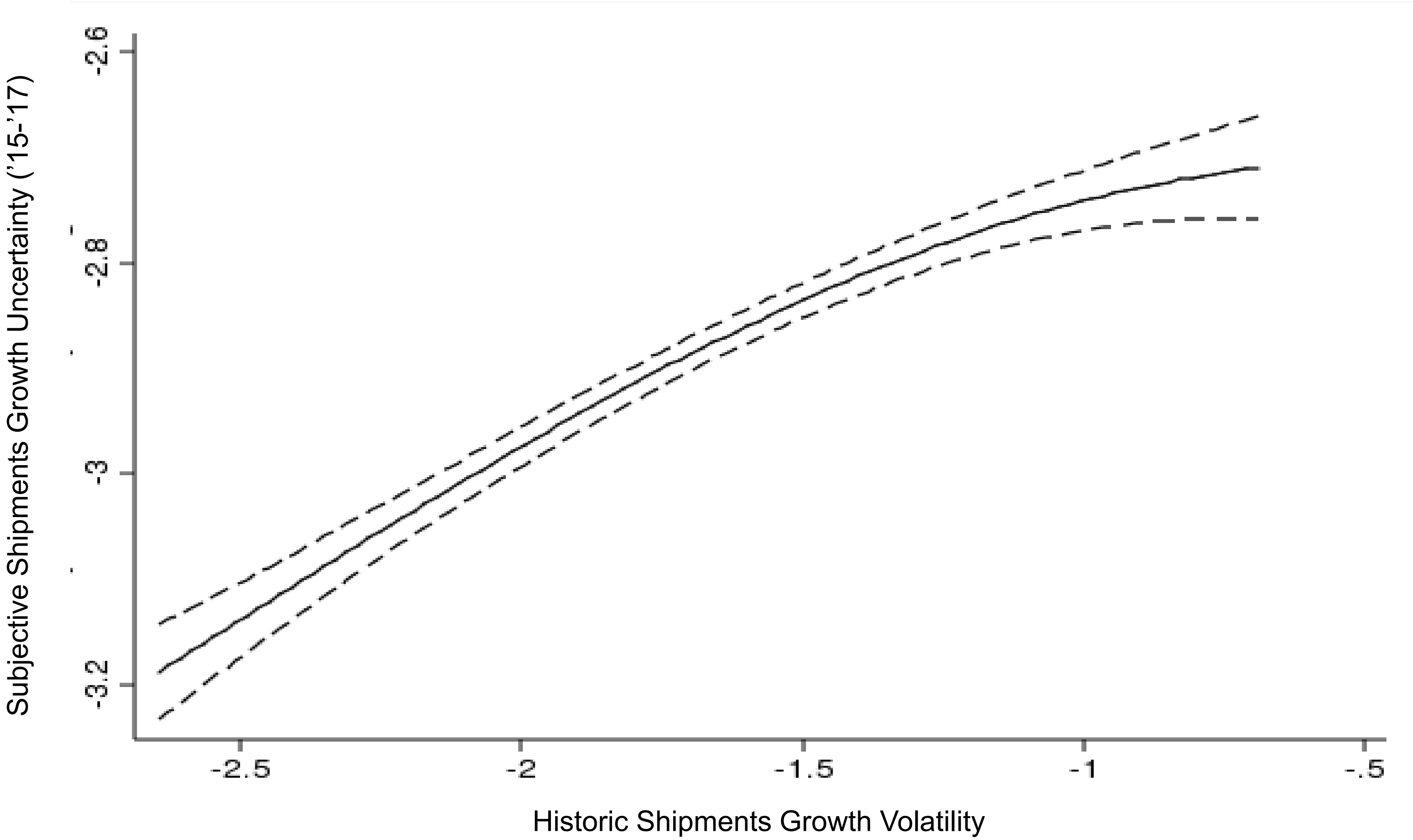
	$Bil.	Mil.	Thou.
For 2015 calendar year		4	500
Estimate for 2016 calendar year		4	750

Example B: Jane also knows that business at Plant A is forecasted to grow approximately an additional 5% in 2017, with predicted annual value of products shipped of $5 million. However, Jane knows there is some uncertainty with that forecast and that the value of products shipped next year could be more or less than $5 million depending on consumer demand, price of materials, and other uncertainties in the market. Given this uncertainty, this is how Jane would complete the following uncertainty forecast table for Plant A's value of products shipped for 2017.

Looking ahead to the 2017 calendar year, what is the approximate dollar value of **products shipped** you would anticipate for this establishment in the following scenarios, <u>and</u> what likelihood do you assign to each scenario?

2017 scenarios, from lowest to highest	Approximate dollar value of shipments in 2017			Percentage likelihood (values in this column should sum to 100)	
	$Bil.	Mil.	Thou.		
LOWEST		2	800	5	%
LOW		4	200	10	%
MEDIUM		5	000	60	%
HIGH		6	300	20	%
HIGHEST		7	500	5	%
			Total	100	%

Figure 2: Shipments Uncertainty vs Historic Shipments Volatility



Notes: The variable on the horizontal axis is the log standard deviation of plant annual shipments growth rates from '04-'05 through '14-'15. The variable on the vertical axis is log standard deviation of plant expectations for shipments growth ('15-'17). The solid line plots the fitted values of a 0^{th} degree local polynomial smoothing of the data. Dashed lines represent 95% confidence intervals.

Table 1: Most Common Probability Distributions (Future Shipments)

Rank			**Probabilities**			**Percent of All Responses**	**Note**
	Lowest	Low	Medium	High	Highest		
1			All Missing			7	
2	5	20	50	20	5	5	
3	5	10	70	10	5	5	
4	5	10	60	20	5	5	vignette
5	20	20	20	20	20	4	uniform
6	10	20	40	20	10	4	
7	5	15	60	15	5	4	
8	10	15	50	15	10	3	
9	10	10	60	10	10	2	
10	5	5	80	5	5	2	
Other:	11.79	15.7	39.29	22.6	13.93	59	

Notes: This table reports common probability distributions in the survey responses for future shipments, ordered from the most common (Rank 1) to the tenth most common (Rank 10).

Table 2: Response characteristics (for future shipments) and their relation to plant characteristics

		Plant characteristics				
	Sample Mean (1)	**Management Practices** (2)	**Log Employment** (3)	**Log Average Earnings** (4)	**Manager Education** (5)	**Multinational Ownership** (6)
A. Response Quality Indicators						
Good response (All three below)	0.85	0.31***	0.31***	0.04***	0.07***	0.02***
Probabilities sum to 100	0.90	0.2***	0.24***	0.05***	0.07***	0.07***
No point mass	0.97	0.45***	0.31***	0.01	0.05***	0.03**
Outcomes weakly monotonic	0.85	0.31***	0.32***	0.04***	0.07***	0.06***
B. Other Response Characteristics						
Interior mode	0.77	0.29***	0.34***	0.05***	0.07***	0.01
Unimodal	0.82	0.21***	0.27***	0.04***	0.06***	0.01*
Symmetric	0.42	0.05***	0.08***	0.03***	0.03***	0.08***
Centered mode	0.62	0.22***	0.29***	0.05***	0.07***	0.03***

Notes: Each response characteristic (e.g. "Probabilities sum to 100", "No point mass", "Outcomes weakly monotonic") equals 1 when the indicated condition holds, 0 otherwise. Column (1) reports sample mean values of the response characteristics. Columns (2) to (6) report slope coefficients in OLS regressions of the indicated response characteristic on the indicated plant characteristic. Management Practices refer to the quality of the plant's management practices, computed as the mean response on several questions in the 2015 MOPS. See Bloom et al. (2013) for details. Employment and Average Earnings are from the 2014 LBD, where the latter measure equals full-year labor costs divided by the mid-March number of employees. Manager Education is the share of managers at the plant with a college degree (bachelors or higher). Multinational Ownership equals 1 if the plant's parent firm also owns foreign production facilities, 0 otherwise. These two variables are also from the 2015 MOPS. ***, ** and * denote significance at the 1, 5 and 10% levels, respectively, using robust standard errors.

Table 3: The first moment of expected growth covaries positively with own recent growth

	Expected plant growth rate from 2015 to 2017 in:							
	Shipments	**Investment**	**Employment**	**Materials**	**Shipments**	**Investment**	**Employment**	**Materials**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Regressors								
Prior Shipments Growth ('14-'15)	0.0702***				0.0576***	0.0561**	0.1036***	0.0659***
	6.4941				4.0042	2.0751	13.4923	5.5294
Prior Investment Growth ('14-'15)		-0.0996***			0.0058**	-0.1003***	0.0108***	0.0068***
		-19.56			2.5130	-19.4271	8.9021	3.5445
Prior Employment Growth ('14-'15)			0.1091***		0.0565***	-0.0374*	0.0567***	0.0442***
			15.8156		4.8029	-1.6870	8.1116	4.4123
Prior Materials Growth ('14-'15)				0.0296***	-0.0137	-0.0053	0.0012	-0.0111
				4.7595	-1.5314	-0.3044	0.2448	-1.4298
Observations	26000	26000	26000	26000	26000	26000	26000	26000
R-squared	0.0035	0.0208	0.0221	0.0020	0.0053	0.0215	0.0461	0.0075

Notes: Table entries report coefficients and t-statistics in plant-level regressions of expected future outcomes on realized past outcomes. Past and expected future growth rates of employment calculated using data for mid-March payroll periods. All other growth rates constructed using annual data. Each column corresponds to a separate regression. ***, ** and * denotes significance at the 1, 5 and 10% levels, respectively, using robust standard errors.

Table 4: Subjective uncertainty over future growth covaries positively with past growth volatility

	Log subjective uncertainty of plant's 2015-2017 growth rate in:								
	Shipments	**Investment**	**Employment**	**Materials**	**Shipments**	**Investment**	**Employment**	**Materials**	**Shipments**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Log Volatility of Past Growth Rates in:									
Plant's shipments	0.2623***				0.1584***	-0.0454**	0.0239	0.0984***	0.1625***
	23.2737				10.2786	-2.4447	1.5996	6.1028	12.2864
Plant's investment expenditures		0.4579***			0.1546***	0.4469***	0.3754***	0.1590***	
		13.3614			5.2452	12.8392	13.4703	5.2730	
Plant's employment			0.3063***		0.0275**	0.0357***	0.2468***	0.0734***	
			32.7114		2.4831	2.6718	23.0300	6.4322	
Plant's expenditures on materials				0.2341***	0.1237***	0.0260	0.0850***	0.1246***	
				20.0824	8.2912	1.4217	5.9656	7.9332	
Shipments of plant's parent firm									0.0760***
									6.2118
Shipments of plant's industry									0.5568***
									15.8372
Observations	18000	18000	18000	18000	18000	18000	18000	18000	18000
R-squared	0.0316	0.0097	0.0613	0.0233	0.0381	0.0103	0.0757	0.0320	0.0479

Notes: Table entries report coefficients and t-statistics in regressions of log subjective uncertainty over the plant's growth rate from 2015 to 2017 on the log volatility of its annual growth rates from 2004-05 through 2014-15. The Column (9) specification also includes log volatility in the growth rates of shipments for the plant's industry and its parent firm. Subjective uncertainty is the standard deviation over future growth rates implied by the 2015 actual value and the plant's probability distribution over 2017 outcomes. Volatility is the log standard deviation of annual growth rates from 2004-05 to 2014-15. To construct the firm-level measure, we average over all plants owned by the parent firm and then compute volatility in the same manner. We construct the plant's industry-level volatility measure in the same manner at the 6-digit NAICS level. The sample contains all plants in the 2015 MOPS with "good responses" to questions about subjective expectations, as defined in Table 2 and all plants with 5+ observations for growth of sales, capital expenditure, employment and materials from 2004-2005 to 2014-2015. ***, ** and * denote 1, 5 and 10% significance levels, respectively, using robust standard errors.

Table 5: Our subjective uncertainty measures covary with common firm- and industry-level uncertainty measures

	Parent Firm	**Parent Firm**	**Median Firm**	**Parent Firm**	**Parent Firm**	**Median Firm**	**Parent Firm**	**Parent Firm**	**Median Firm**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Realized stock market volatility	0.1167***	0.0720**	0.2127***						
	2.9171	1.9887	4.3688						
Options-implied volatility				0.2119***	0.1194**	0.2247***			
				3.4128	2.2278	3.2363			
Forecaster disagreement							0.1139***	0.0608**	0.0867***
							3.6752	2.1392	3.1663
Industry fixed effects	N	Y	n/a	N	Y	n/a	N	Y	n/a
Plant controls	N	Y	Y	N	Y	Y	N	Y	Y
Observations	5000	5000	26000	5000	5000	26000	5000	5000	26000
R-squared	0.0044	0.0741	0.0056	0.0063	0.0751	0.0046	0.0092	0.0753	0.0065

Notes: Table entries report regresssions of plant-level subjective uncertainty on firm-level measures of volatility or disagreement. Subjective uncertainty is the log standard deviation of the plant's 2015-2017 shipments growth rate. "Realized stock market volatility" is the log standard deviation of the firm's daily stock returns in 2014, the year before the MOPS survey. "Option-implied volatility" is the firm's mean 91-day option-implied volatility in 2016. "Forecaster disagreement" is the coefficient of variation of analysts' 2016 forecasts of firm-level earnings per share. "Parent Firm" denotes a regression of subjective uncertainty on volatility or disagreement of the plant's parent firm, for plants with a publicly listed parent firm matched to Compustat data. "Median Firm" denotes a regression of subjective uncertainty on the median volatility or disagreement among publicly listed firms in the same 6-digit NAICS industry as the plant. Using the median firm lets us expand the sample to all plants with a "Good Response," as defined in Table 2. ***, ** and * denote significance at the 1,5, and 10% levels, respectively, using robust standard errors. We report the *t* statistic beneath each coefficient estimate.

Table A1: The Most Common Titles and Categories of MOPS Contacts

Panel A: Categories	**Share**
Manager (except CEO)	53%
Finance (except CFO)	23%
CEO	8%
CFO	5%
HR/admin (non manager)	4%
Missing	6%

Panel B: Titles	**Share**
Plant manager	13%
Financial controller	10%
CEO	6%
CFO	4%
General manager	3%
Other (e.g. vice-president of engineering, COO or production manager)	64%

Table A2: Pairwise correlations

Panel A: Mean expected growth rates ('15-'17)				
	Shipments	**Investment**	**Employment**	**Materials**
Shipments	1			
Investment	0.1338	1		
Employment	0.3186	0.1066	1	
Materials	0.4072	0.1286	0.3736	1

Panel B: Standard deviation of expected growth rates ('15-'17)				
	Shipments	**Investment**	**Employment**	**Materials**
Shipments	1			
Investment	0.2402	1		
Employment	0.4501	0.2639	1	
Materials	0.5543	0.2854	0.4890	1

Panel C: Skewness of expected growth rates ('15-'17)				
	Shipments	**Investment**	**Employment**	**Materials**
Shipments	1			
Investment	0.1730	1		
Employment	0.1950	0.1394	1	
Materials	0.3447	0.1757	0.2312	1