Investment and Subjective Uncertainty[1]

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Abstract: A longstanding challenge in evaluating the impact of uncertainty on investment is obtaining measures of managers' subjective uncertainty. We address this challenge by using a detailed survey measure of uncertainty collected by the U.S. Census Bureau for approximately 25,000 manufacturing plants. We find three key results. First, investment is negatively associated with higher uncertainty. Second, uncertainty is also negatively related to employment growth and overall shipments growth, which highlights the damaging impact of uncertainty. Third, rental capital and temporary workers are positively correlated with uncertainty, demonstrating that businesses switch from less flexible to more flexible inputs under uncertainty.

Keywords: Subjective expectations, business-level uncertainty

JEL Classification: L2, M2, O32, O33.

The data that support the findings of this study are available from the U.S. Census Bureau to researchers on approved projects through the Federal Statistical Research Data Centers. For more information see https://www.census.gov/about/adrm/fsrdc.html.

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Introduction

There is a long literature trying to estimate the impact of uncertainty on investment. One of the major challenges in doing this is obtaining measures of uncertainty as perceived by the manager.[2] The literature often uses proxies like stock-market volatility (e.g., Leahy and Whited 1996 or Bloom, Bond, and Van Reenen 2007), sales and investment volatility (Bachman and Bayer 2014), implied-volatility (e.g., Dew-Becker and Giglio 2023), earnings calls (Hassan, et al. 2019), SEC filings (Handley and Li 2020), newspapers (e.g., Baker, Bloom, and Davis 2016) or various macro measures of uncertainty (e.g., Jurado, Ludvigson, and Ng 2015). Despite the availability of these proxies, none of these measures provide a direct measure of managers' actual subjective uncertainty.

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).[3] MOPS is the first large-scale survey of management practices in the United States, covering more than 30,000 plants across more than 10,000 firms. It has been conducted in three waves, for reference periods 2010, 2015, and 2021.[4] The sample size and high survey response rate, the use of the establishment within the firm as the response unit, the ability to link to other Census Bureau data, and comprehensive coverage of manufacturing industries make the MOPS dataset unique. As part of the 2015 MOPS, we asked questions regarding plant-level expectations of own current-year and future outcomes for shipments (sales).

[2] See Hayashi (1982) and Abel and Blanchard (1986) for classic contributions on modelling business expectations in dynamic models of investment. The importance of expectations in the modelling of business decision making is widely recognized (see, for example, Caballero 1999, Chirinko 1993, and Dixit and Pindyck 1994).

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

[4] See the descriptions of MOPS in Bloom, et al. (2019) and Buffington, et al. (2017).

The survey questions elicit point estimates for current-year (2016) outcomes and five-point probability distributions over next-year (2017) outcomes, yielding a much richer and more detailed dataset on business-level expectations and subjective uncertainty than previous work, and for a much larger sample.[5]

Among plants in the 2015 MOPS publication sample, we find that 85 percent provide logically sensible responses to our five-bin questions, suggesting that most managers can form and express detailed subjective probability distributions. First and second moments of plant-level subjective probability distributions covary strongly with first and second moments of historical outcomes, suggesting that our subjective expectations data are well-founded. Having established the validity of these measures, we take the first and second moments of the plants' subjective probability distributions as measures of plant-level expectations and subjective uncertainty, respectively. Aggregating the subjective uncertainty measure to the firm level, we also find uncertainty correlates positively with realized stock-return volatility, option-implied volatility, and analyst disagreement about future earnings per share for the firm and for the median publicly listed firm in the firm's industry, helping to validate these popular firm-level measures of uncertainty.

The MOPS is a mandatory supplement to the 2015 Annual Survey of Manufactures (ASM) and is mailed to the physical address of all plants in the ASM sample. Each of the variables for which we elicit forecasts on the MOPS is also included on the ASM and the quinquennial Census of Manufactures (CMF). As a result, we can match the MOPS forecasts to realized values in subsequent years. Using these realized values, we find that forecasts are also highly predictive of

[5] Guiso and Parigi (1999) and Bontempi, Golinelli, and Parigi (2010) use three-point probability distributions from a survey of about 1,000 Italian firms per year from 1994 to 2006. Masayuki (2013) uses two-point distributions from a survey of 294 Japanese firms in 2013. Bachmann, et al. (2021) use the span between best- and worst-case scenarios to quantify subjective uncertainty using German quarterly firm data for 2013 to 2016. See Manski (2018) for additional discussion and references to previous efforts to measure business and household expectations.

outcomes, suggesting managers are providing well-considered responses.

Armed with our measure of subjective shipments growth uncertainty, we evaluate how uncertainty is linked to investment, employment, shipments, and input growth. The sign of this link is theoretically ambiguous – while a large literature highlights the potential negative impact of uncertainty on investment (see, for example, Bernanke 1983 and Dixit and Pindyck 1994), a long time to build (Bar-Ilan and Strange 1996) or competition for innovation (Weeds 2002) could alter this prediction. In our empirical analysis we find three key stylized facts. First, investment is strongly and robustly negatively associated with higher uncertainty, with a two standard deviation increase in uncertainty associated with about a six percent reduction in investment. Second, uncertainty is also negatively related to employment growth and overall shipments growth, which highlights the damaging impact of uncertainty on firm growth. Third, flexible inputs like rental capital and temporary workers show a positive relationship to uncertainty, showing how firms switch from less to more flexible factors at higher levels of uncertainty.

The paper proceeds as follows. Section 2 discusses the MOPS sample and measurement of plant-level expectations, and reports results confirming firms provide reasonable subjective shipments probability distributions. Section 3 examines how subjective uncertainty is associated with investment, employment, shipments, and flexible input growth. Section 4 concludes.

Measuring Business Expectations and Uncertainty

The 2015 wave of the Management and Organizational Practices Survey (MOPS) was mailed to the physical address of manufacturing establishments to the attention of the "plant manager" in

April 2016 as a mandatory supplement to the 2015 Annual Survey of Manufacturers (ASM).[6] This plant-level survey contained a range of questions about management and organizational practices, plus some questions on background characteristics and, importantly for this paper, a section on "Uncertainty." This contained eight questions on plants' expectations for 2016 and 2017 over four outcomes: shipments, investment expenditures, employment, and materials expenditures. In this paper we will use the question on shipments to generate measures of first- and second-moment expectations of managers (expected growth and subjective uncertainty). The MOPS also contains a question for the "name of [a] person to contact regarding this report" as well as that person's title. This certification data indicates the 2015 MOPS survey was typically answered by senior plant management, in that the most common position title of the contact's name is "plant manager" (13 percent), "financial controller" (ten percent) or "CEO" (eight percent), with about 90 percent within broad categories of "management" or "finance."

The MOPS could be completed either using an electronic survey instrument or by returning the paper survey form by mail. Most respondents (80 percent) 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.

Our uncertainty module starts by discussing our two types of measures of expectations. 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*

[6] For more details see Buffington, et al. (2017), Buffington, Hennessy, and Ohlmacher (2018), and https://www.census.gov/programs-surveys/mops/technical-documentation/methodology.html. Note that the ASM is a retrospective survey, so the April 2016 survey wave asked about data for calendar year 2015.

transfers, exports and other receipts at this establishment? Exclude freight and excise taxes?"[7] 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.[8] 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 for the corresponding probabilities such that they add to 100 percent. 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 front of the survey and the key survey question. The idea behind this question is to collect probability distributions over own-plant outcomes. The five-bin structure outcome and probability structure offer 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.[9] It is also extremely flexible in that respondents have nine degrees of freedom to characterize their expectations – five outcomes and five probabilities, less one restriction that the probabilities add to 100 percent.

Our key establishment-level uncertainty measure is the subjective uncertainty regarding shipment growth. We consider it to be the closest proxy in our data to uncertainty in a Dixit-

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[7] 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

[8] Because the 2015 ASM asked for the value of shipments for the same respondents, this also provides a metric for measurement error in the survey.

[9] Bloom and Davis worked with a team at the Atlanta Fed to develop a similar survey on a smaller panel of around 1,750 firms to collect monthly expectations data over time, and to provide first and second moment aggregate indicators to help inform monetary policy. See Altig, et al. (2022), for details about the Atlanta Fed survey, and Barrero (2022) for results from this survey. See Bloom, et al. (2019) for a similar application in a Bank of England UK survey. For information on the cognitive testing process for the MOPS, see Buffington, Herrell, and Ohlmacher (2016).

Pindyck model.[10] We create our measures of subjective shipments uncertainty for each MOPS respondent based on the standard deviation of the establishment's growth rate based on actual shipments in 2015 as reported on the MOPS and the set of five forecasted values. Specifically, it is measured as the standard deviation of the plant's predicted annual growth rates 2015-2017 (over the five bins). Thus, for establishment i:

$$Subjective\ Uncertainty_i = \sqrt{\sum_{j=1}^{5} P_{ij}\left(g_{ij} - \bar{g_i}\right)^2}, \text{and } \bar{g_i} = \sum_{j=1}^{5} P_{ij} g_{ij},$$

where g_{ij} is the forecasted growth for scenario j made by the manager in establishment i, and P_{ij} is the probability that this manager assigned to scenario j. We use $\bar{g_i}$ as the first moment forecast for shipment growth. While we use the point forecast for 2016 in the data construction and cleaning process, our outcome variables for subjective expectations and uncertainty always use the 2017 questions. We measure volatility of historical growth rates, or the variation over realized values, as the standard deviation of the establishment's annual growth rates for all years from 2004-2015, as available.

Sample

Of the approximately 50,000 plants in the MOPS mail sample, about 35,000 establishments returned responses. Table 1 reports the ten most common subjective probability distributions elicited by the question on future shipments. About seven percent of all respondents fail to answer the five-bin questions about future shipments, which we interpret as an inability or unwillingness

[10] As we report in Table A2 of Bloom, et al. (2020), sales uncertainty is highly correlated with employment and materials uncertainty (correlation of about 0.5 or higher). While subjective uncertainty about investment looks quite different compared to the other measures, this is at least partly driven by the lumpiness of investment, with high frequency of zero investment reporting (see for example Cooper and Haltiwanger 2006).

to express subjective probability distributions.[11] Not responding could also reflect an extreme version of uncertainty, and the inability to forecast the likelihood of future events (Knightian uncertainty). However, we find this less plausible in our context, given the relatively short run (one year ahead) forecasted elicited in our survey. Rows (2) to (10) report the next nine most common probability distributions, most having a central mode. As seen in Row 5, about four percent of respondents report a uniform probability distribution for future shipments. Row 4 shows that only five percent or less of respondents provide vignette probabilities when answering the uncertainty questions, suggesting that anchoring effects are small.

For the analysis, we keep responses which we defined in Bloom, et al. (2020) as "good," which means they have a non-degenerate probability distribution, a total probability that adds to between 90 percent and 110 percent, and a monotonic progression of variables corresponding with lowest to highest shipments (see Appendix for details). 85 percent of respondents meet all three requirements for a "good response" for the question regarding future shipments. Our final sample consists of approximately 25,000 businesses with "good" responses to all the uncertainty questions, which we can also match to the ASM information in 2015, 2016 and 2017 on shipments, investment, employment and other outcomes. Table 2 reports the descriptive statistics for our final sample, showing the plants have declines of about 1.7 percent for annualized shipments growth and of about 2.6 percent for employment growth. Their subjective shipments uncertainty is about nine percent, roughly a quarter of the annualized stock returns volatility of a publicly listed company.

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

Validating Our Expectations Data

We start with a graphical representation showing the tight relation between expectations and realizations. Figure 2 plots the expected shipments growth on the x-axis and realized shipments growth on the y-axis. Expected growth is measured using the 2015 value from the MOPS and the 2017 forecast from the MOPS. In contrast, the realized growth rate is measured using the ASM (2015) and CMF (2017). Each of the 50 dots on the plot is the mean of approximately 500 plants.[12] The plot shows a clear positive relationship, which suggests that forecasts are strongly predictive of outcomes.

Our data also allows us to evaluate the relationship between forecast accuracy and uncertainty. Defining the expectation error as the difference between expected and realized growth over the 2015-2017 horizon, we can ask, is high subjective uncertainty predictive of large expectation errors? In Figure 3, we see that the magnitude of the expectation error, measured as the absolute value of difference between expected and realized 2015-2017 shipments growth is increasing in the plant's subjective uncertainty. This is a striking relationship – plants that provide more dispersed forecasts have significantly larger expectation errors in absolute value.

Next, we compare our measures of subjective uncertainty with commonly used measures, showing that these are tightly related. The three firm-specific proxies for uncertainty that we consider are (a) realized stock returns volatility, (b) options-implied volatility, and (c) forecaster disagreement. For this analysis, we aggregate the Census data to the firm-level by taking the employment-weighted mean of establishment-level log of subjective uncertainty (the standard

[12] Census disclosure protocols do not permit scatterplots of individual observations, hence throughout we provide binned scatterplots instead. Our binned scatter plots are generated by first splitting the x-axis variable to 50 equal bins, then drawing the average of the y variable for each of these bins. We follow the same procedure in Figures 3 and 4 (with 25 bins for the latter).

deviation of the plant's predicted annual growth rates 2015-2017 over the five bins). We then match these measures to stock market data on publicly listed firms, which yields a sample of approximately 750 firms with approximately 5,100 underlying plants.

In column (1) of Table 3 we regress firm subjective shipments growth uncertainty on the log standard deviation of daily stock returns of the firm over the prior year. Daily stock returns are a common measure of firm uncertainty, used by dozens of papers starting with Leahy and Whited (1996). We find there is a strong positive relationship between the two. In columns (2) and (3) we conduct the analysis at the industry-level by regressing firm uncertainty on the median log standard deviation of daily stock returns in 2014 for the firms within the same industry. Since this specification does not require us to match to firm-specific data on publicly listed firms, the sample in column (2) is the full sample of firms with 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 the one-percent 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. The industry proxies allow us to verify that the relation between subjective uncertainty and realized volatility is similar for privately held firms, for which we do not have firm-level stock data (column 3).

Columns (4) through (9) show that the strong link with subjective uncertainty is maintained when using other commonly used uncertainty measures including option-implied volatility (used for example by Paddock, Siegel, and Smith 1988, Bloom 2009, and Kellogg 2014) and forecaster disagreement (see, for example, Bachman, Elstner, and Sims 2013, Bond and Cummins 2004, and

Xiao 2016).[13]

Uncertainty and Investment

Table 4 presents our key results, investigating the relationship between plant-level investment and managers' subjective uncertainty. The table reports results from a regression of investment, measured as capital expenditure in 2017 over capital stock in 2016, on expectation and uncertainty measures. In column (1) we see that expected shipments growth rates derived from the managers forecasts have a strongly significant relationship with investment. The point estimate of 0.044 implies that a two standard-deviation increase in shipments growth expectations is associated with an increase in investment of 1.7 percentage points, a large and significant relationship.

In column (2) we use our main variable of interest and find a significant negative relationship as predicted by the investment and uncertainty literature following Bernanke (1983) and Dixit and Pindyck (1994). These results are consistent with the findings in Guiso and Parigi (1999) but are estimated with a large sample and using detailed measures of managers' subjective uncertainty. We find that a two standard-deviation increase in shipments growth uncertainty is associated with a 0.53 pp. decrease in investment rate. This is about six percent of the mean investment rate for 2016 in our sample and is comparable to the decline in investment in a typical post-war recession in the US.[14]

In columns (3) and (4) we include both our first and second moment measures (expected shipments growth and subjective shipments uncertainty) without controls and then with controls for industry and survey noise and find very similar results.

[13] See, for example, the survey of measures of uncertainty in Bloom (2014).
[14] The median (mean) real investment decline in the first quarter of post-war recessions in the US is 3.3 percent (4.8 percent).

We investigate the robustness of this result in Table 5 by adding measures of expected shipments skewness in column (2) without finding any material impact.[15] In column (3) we include a measure for prior shipments growth finding this is highly significant, noting our main expectations and uncertainty measures retain similar coefficients as before. In column (4) we also include lagged shipments volatility in case uncertainty is simply proxying for lagged volatility, but we find that both measures are highly significant and negative. Finally, in column (5) we add the lagged realizations of growth rates and volatility finding, as before, a clear positive impact of the first moment of expected shipments growth and a negative impact of the second moment on investment rates.

In Table 6 we move from investment to consider employment growth. Employment is another factor which is costly to adjust, as long emphasized in the literature stretching from Oi (1961) to Nickell (1986) to Bertola and Bentolila (1990). As a result, increases in uncertainty should lead to a pause in hiring as firms act more cautiously, generating a reduction in employment as workers naturally attrit and are not replaced. This is exactly what we see in columns (1) to (4), in that while expected shipments growth (the first moment) is positively correlated with employment growth, subjective shipments uncertainty (the second moment) is negatively correlated with employment growth.

Table 7 examines the relationship of subjective uncertainty directly with shipments growth, which given the negative relationship with capital and labor inputs is likely to also be negative. Indeed, we see that is the case, with columns (1) to (4) confirming a positive relationship with expected and realized shipments growth, and a negative relationship between subjective shipments

[15] We should note that with a five-bin distribution where the lowest and highest bins typically have about a ten percent probability weight detecting skewness is hard, so the insignificant result may simply reflect a high level of measurement error in our skewness variable.

growth uncertainty and realized shipments growth. The real-options channel of uncertainty would predict this negative relationship, whereby firms become increasingly cautious at higher levels of uncertainty, pausing both investment and hiring, which reduces capital and labor inputs, reducing shipments levels.

Table 8 examines two more flexible input factors – rental capital and temporary workers. For these we see different results. In columns (1) and (2) we observe a positive relationship between rental capital input growth and uncertainty. The rationalization for this is that when uncertainty is high, firms cut-back on investment due to the classic real-options channel whereby higher uncertainty makes them more cautious about making partially irreversible investment decisions. However, rental capital, while typically being more expensive on a weekly basis, usually has far lower costs of adjustment in that rented capital is usually costless to return to the rental provider. As such, when uncertainty is high, firms will switch capital inputs from their own investments to external rented capital, consistent with the positive relationship between uncertainty and rental capital demand. In columns (3) and (4) we look at temporary workers finding a similarly positive, albeit insignificant, relationship with uncertainty, suggesting at higher levels of uncertainty firms are somewhat more inclined to employ temporary than permanent workers.

The main results discussed in this section are collectively shown in the form of a binned scatterplot in Figure 4, which plots investment, employment growth, shipments growth and rental investment against subjective uncertainty.[16] We see the first three yield strong negative relationships while the final one yields a strong positive relationship. Input factors with high levels of adjustment costs see lower growth levels when uncertainty increases, while flexible input

[16] The definitions of employment and sales growth in the figures are identical to the ones used in Tables 6 and 7 respectively. For investment and rental capital, we used the 2016 quantities over the 2015 stock. Due to limited Census data access through COVID we were not able to update these figures when the 2017 data became available.

factors can increase as they provide a valuable hedge against negative demand shocks.

Conclusions

The 2015 MOPS, fielded as a partnership between the U.S. Census Bureau and external researchers, included innovative questions asking plants to provide five-bin outcome and probability forecasts over future shipments. Analysis of responses from approximately 25,000 manufacturing plants shows three key results. First, investment is strongly and robustly negatively associated with higher uncertainty, with a two standard deviation increase in uncertainty associated with about six percent reduction in investment. Second, uncertainty is also negatively related to employment growth and overall shipments (sales) growth, which highlights the damaging impact of uncertainty on firm growth. Third, flexible inputs like rental capital and temporary workers show a positive relationship to uncertainty, showing how firms switch from less to more flexible factors at higher levels of uncertainty.

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 zero to five) and probabilities (ranges from zero to five).
2. Flag response patterns that are "1, 2, 3, 4, 5" and where the value of the point estimate for 2016 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 ten 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 ten 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 percent assigned to any outcome.

14. Create an indicator variable for "good" responses. The indicator is equal to one if all the following hold:
    a. Outcome distribution is weakly increasing.
    b. More than one scenario is reported.
    c. Probability distribution does not have 100 percent 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 + |high – 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 - |low – 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 percent. 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 percent. Furthermore, probabilities less than zero or greater than 100 could not be entered in the online form.

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Table 1: Most Common Probability Distributions (Future Shipments)

Rank			**Probabilities**			**Percent of**
	Lowest	Low	Medium	High	Highest	**Responses**
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
5	20	20	20	20	20	4
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: The common probability distributions in the survey responses for future shipments, ordered from the most common (rank 1) to the tenth most common (rank 10). Row 4 is the vignette distribution, and row 5 is the uniform distribution

Table 2: Sample statistics

Variable	Mean	S.D.
(Capital expenditures, 2016)/(Capital stock, 2015)	0.085	0.106
(Rental capital expenditures, 2016)/(Capital stock, 2015)	0.054	0.101
Growth rate of employment, 2015-2017	-0.026	0.359
Growth rate of shipments, 2015-2017	-0.017	0.369
Log(value added/employment), 2017	5.024	0.859
Expected value of 2015-2017 shipments growth rate	0.028	0.193
Standard deviation of 2015-2017 shipments growth rate forecast	0.092	0.085
Absolute expectation error for 2015-2017 shipments growth rate	0.263	0.337
N=25000		

Table 3: Our subjective uncertainty measures covary with parent firm uncertainty measures

	Public	**All**	**Private**	**Public**	**All**	**Private**	**Public**	**All**	**Private**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Firm Realized Volatility Stock Returns	0.2713***								
	(0.0587)								
Industry Realized Volatility Stock Returns		0.1756***	0.1649***						
		(0.0293)	(0.0301)						
Firm Options-Implied Volatility				0.3091***					
				(0.0692)					
Industry Options-Implied Volatility					0.2422***	0.2320***			
					(0.037)	(0.0383)			
Firm Forecaster Disagreement							0.1167***		
							(0.0383)		
Industry Forecaster Disagreement								0.0659***	0.0614***
								(0.0122)	(0.0125)
Firms	750	16000	15000	750	16000	15000	300	16000	15000
Underlying Plants	5100	26000	21000	5100	26000	21000	3500	26000	21000
R-squared	0.0856	0.0657	0.0624	0.0792	0.0661	0.0627	0.085	0.0652	0.0618

Notes: Table entries report regressions of firm-level subjective uncertainty on firm-level measures of volatility or disagreement. All regressions include firm-level controls for employment-weighted mean establishment adoption of structured management practices, employment-weighted mean establishment employment, employment-weighted mean establishment age, and employment weighted mean establishment share of managers with a bachelor's degree. Plant-level subjective uncertainty is the log standard deviation of the plant's 2015-2017 shipments growth rate. Firm-level subjective uncertainty is the employment-weighted mean of plant-level uncertainty for all plants in the sample sharing the same parent firm. "Firm realized stock market volatility" is the log standard deviation of the firm's daily stock returns in 2014, the year before the MOPS survey. "Firm options-implied volatility" is the firm's mean 91-day option-implied volatility in 2016. "Firm forecaster disagreement" is the coefficient of variation of analysts' 2016 forecasts of firm-level earnings per share. "Industry" measures of volatility or disagreement is the median volatility or disagreement among publicly listed firms in the same 4-digit NAICS industry as the plant. "Public" denotes a regression of subjective uncertainty on volatility or disagreement on the sample of publicly listed parent firms matched to Compustat data. "All" denotes a regression of subjective uncertainty on volatility or disagreement on the sample of parent firms for all plants with a "Good Response," as defined in Table 2. "Private" denotes a regression of subjective uncertainty on volatility or disagreement on the sample of firms in "All" that were not matched to Compustat data. That is, in general the sample in columns labeled "All" is the union of the samples used in the "Public" and "Private" regressions. Due to Census Bureau rounding rules, the reported firm counts for the "Public" and "Private" samples do not sum to the reported firm count for the "All" sample. In column (7), the resulting sample of "Public" firms is smaller than in columns (1) and (4) because we require more than one forecast at the firm-level. ***, ** and * denote significance at the 1,5, and 10% levels, respectively.

Table 4: Investment rate and uncertainty

Dep Var: (I_t/K_{t-1})	(1)	(2)	(7)	(8)
Expected Sales Growth$_{t-2}$	0.0439***		0.0431***	0.0401***
	(0.0036)		(0.0036)	(0.0037)
Uncertainty of Sales Growth$_{t-2}$		-0.0312***	-0.0225***	-0.0276***
		(0.0073)	(0.0075)	(0.0077)
Industry FE	N	N	N	Y
Noise Controls	N	N	N	Y
Observations (establishments)	25000	25000	25000	25000
R-squared	0.007	0.001	0.007	0.036

Notes: Table entries report coefficients and standard errors from OLS regressions of (capital expenditure in 2017)/(capital stock in 2016) on sales expectations, and subjective uncertainty from the MOPS 2015 survey. 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. Industry FE are 5-digit NAICS dummies. Noise controls include respondent position, tenure, measurement error (the average difference between 2015 values of shipments and employment between MOPS and ASM), month submitted, source (internet/paper). ***, **, and * denote 1, 5, and 10% significance levels, respectively. Firm and observation counts rounded to comply with Census Bureau rules on disclosure avoidance.

Table 5: Robustness of Investment Regressions

Dep Var: (I_t/K_{t-1})	(1)	(2)	(3)	(4)	(5)
Expected Sales Growth$_{t-2}$	0.0401***	0.0397***	0.0380***	0.0421***	0.0409***
	(0.0037)	(0.0037)	(0.0037)	(0.0044)	(0.0044)
Uncertainty of Sales Growth$_{t-2}$	-0.0276***	-0.0281***	-0.02312***	-0.0279***	-0.0228**
	(0.0077)	(0.0077)	(0.0077)	(0.0095)	(0.0095)
Skewness of Sales Growth$_{t-2}$		-0.0008			
		(0.0007)			
Prior Shipments Growth ('14-'15)			0.0265***		0.0267***
			(0.0027)		(0.0034)
Log Volatility of Past Growth Rates for Plant's Shipments				-0.0030**	-0.0030**
				(0.0013)	(0.0013)
Industry FE	Y	Y	Y	Y	Y
Noise Controls	Y	Y	Y	Y	Y
Observations (establishments)	25000	25000	25000	17000	17000
R-squared	0.036	0.036	0.041	0.05	0.054

Notes: Table entries report coefficients and standard errors from OLS regressions of (capital expenditure in 2017)/(capital stock in 2016) on sales expectations, subjective uncertainty, and the skewness of expectations from the MOPS 2015 survey. 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. Industry FE are 5-digit NAICS dummies. Noise controls include respondent position, tenure, measurement error (the average difference between 2015 values of shipments and employment between MOPS and ASM), month submitted, source (internet/paper). ***, **, and * denote 1, 5, and 10% significance levels, respectively. Firm and observation counts rounded to comply with Census Bureau rules on disclosure avoidance.

Table 6: Employment growth and Uncertainty

Dep Var: Employment growth	(1)	(2)	(3)	(4)
Expected Sales Growth$_{t-2}$	0.2674***		0.2575***	0.2359***
	(0.0145)		(0.0145)	(0.0148)
Uncertainty Of Sales Growth$_{t-2}$		-0.3080***	-0.2561***	-0.1809***
		(0.0351)	(0.0353)	(0.0362)
Industry FE	No	No	No	Yes
Noise Controls	No	No	No	Yes
Observations (establishments)	25000	25000	25000	25000

Notes: Table entries report coefficients and standard errors from OLS regressions of employment growth (between 2017 and 2015) against sales expectations and subjective uncertainty from the MOPS 2015 survey. 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. Industry FE are 5-digit NAICS dummies. Noise controls include respondent position, tenure, measurement error variable (the average difference between 2015 values of shipments and employment between MOPS and ASM), month submitted, source (internet/paper). All growth rates between t-1 and t are calculated as $2(x_t-x_{t-1})/(x_t+x_{t-1})$. ***, ** and * denote 1, 5 and 10% significance levels, respectively.

Table 7: Sales growth and uncertainty

Dep Var: Sales growth rate	(1)	(2)	(3)	(4)
Expected Sales Growth$_{t-2}$	0.4345***		0.4146***	0.3903***
	(0.0153)		(0.0154)	(0.0158)
Uncertainty Of Sales Growth$_{t-2}$		-0.1984***	-0.1690***	-0.1595***
		(0.0361)	(0.0361)	(0.0368)
Industry FE	No	No	No	Yes
Noise Controls	No	No	No	Yes
Observations (establishments)	25000	25000	25000	25000

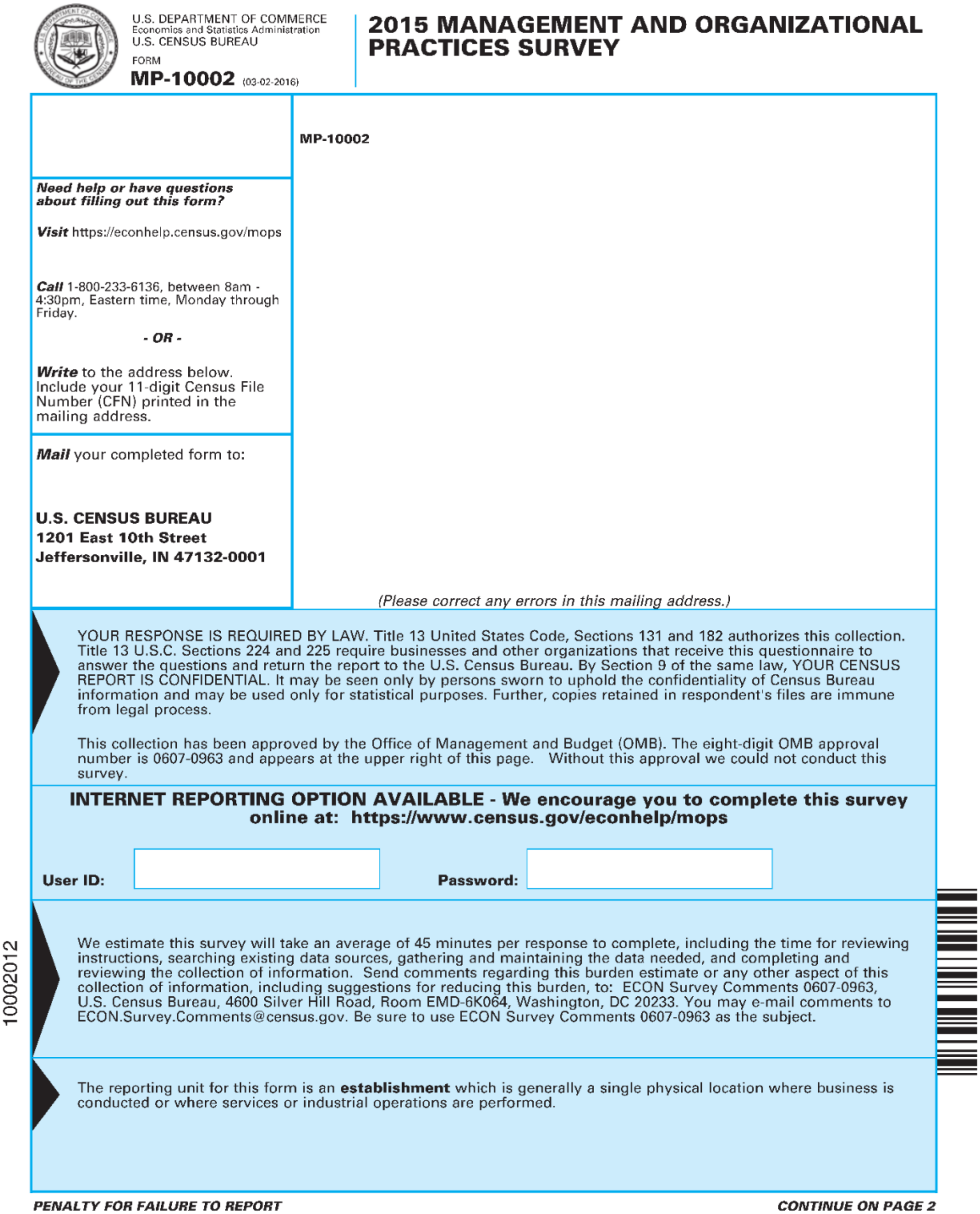
Notes: Table entries report coefficients and standard errors from OLS regressions of sales growth (between 2017 and 2015) against sales expectations and subjective uncertainty from the MOPS 2015 survey. Subjective uncertainty is the standard deviation over future growth rates implied by the 2015 actual value and the plant's probability distribution over 2017 outcomes. Industry FE are 5-digit NAICS dummies. Noise controls include respondent position, tenure, measurement error variable (the average difference between 2015 values of shipments and employment between MOPS and ASM), month submitted, source (internet/paper). All growth rates between t-1 and t are calculated as $2(x_t-x_{t-1})/(x_t+x_{t-1})$. ***, ** and * denote 1, 5 and 10% significance levels, respectively.

Table 8: Flexible factors and uncertainty

	Rental capital rate (RI_t/K_{t-1})		Temp workers growth	
Dep Var:	(1)	(2)	(3)	(4)
Expected Sales Growth$_{t-2}$	0.0340***	0.0236***	0.0229***	0.0213***
	(0.0035)	(0.0039)	(0.0027)	(0.0028)
Uncertainty Of Sales Growth$_{t-2}$	0.0681***	0.0396***	0.0009	0.0027
	(0.0087)	(0.0086)	(0.0053)	(0.0055)
Industry FE	No	Yes	No	Yes
Noise Controls	No	Yes	No	Yes
Observations (establishments)	25000	25000	25000	25000

Notes: All regressions are OLS. First two columns report coefficients and standard errors from regressions of (capital rental in 2017)/(capital stock in 2016) against sales expectations and subjective uncertainty from the MOPS 2015 survey. Columns 3 and 4 report results from regressions of growth in temporary workers against sales expectations and subjective uncertainty. Industry FE are 5-digit NAICS dummies. Noise controls include respondent position, tenure, measurement error variable (the average difference between 2015 values of shipments and employment between MOPS and ASM), month submitted, source (internet/paper). All growth rates between t-1 and t are calculated as $2(x_t-x_{t-1})/(x_t+x_{t-1})$. ***, ** and * denote 1, 5 and 10% significance levels.

Figure 1: The MOPS mandatory survey and key sales expectations question



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The reporting unit for this form is an **establishment** which is generally a single physical location where business is conducted or where services or industrial operations are performed.

PENALTY FOR FAILURE TO REPORT

CONTINUE ON PAGE 2

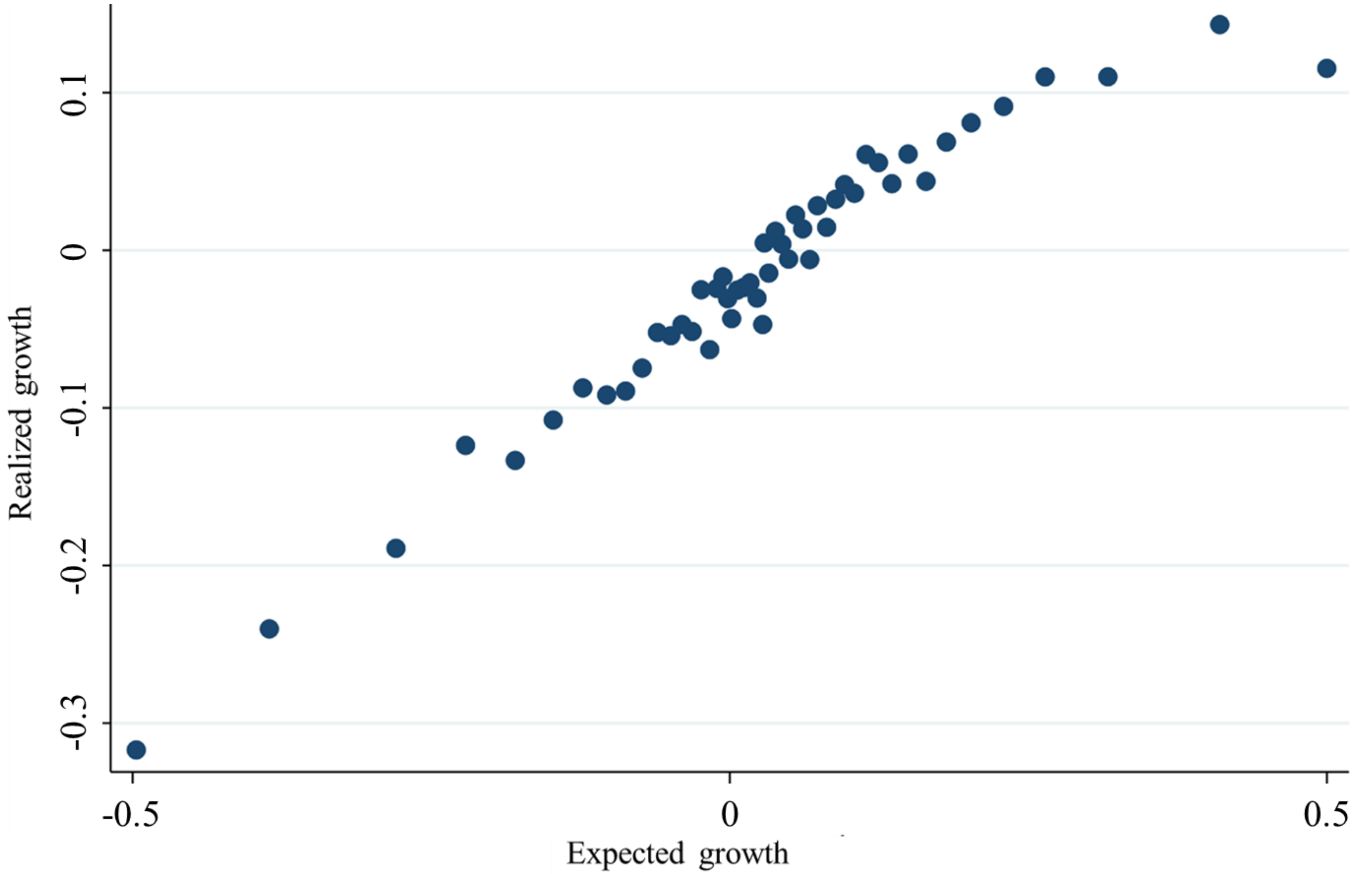
30 For calendar years 2015 and 2016, what are the approximate dollar values of **products shipped**, including interplant transfers, exports and other receipts at this establishment? Exclude freight charges and excise taxes.

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

31 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, and what likelihood do you assign to each scenario?

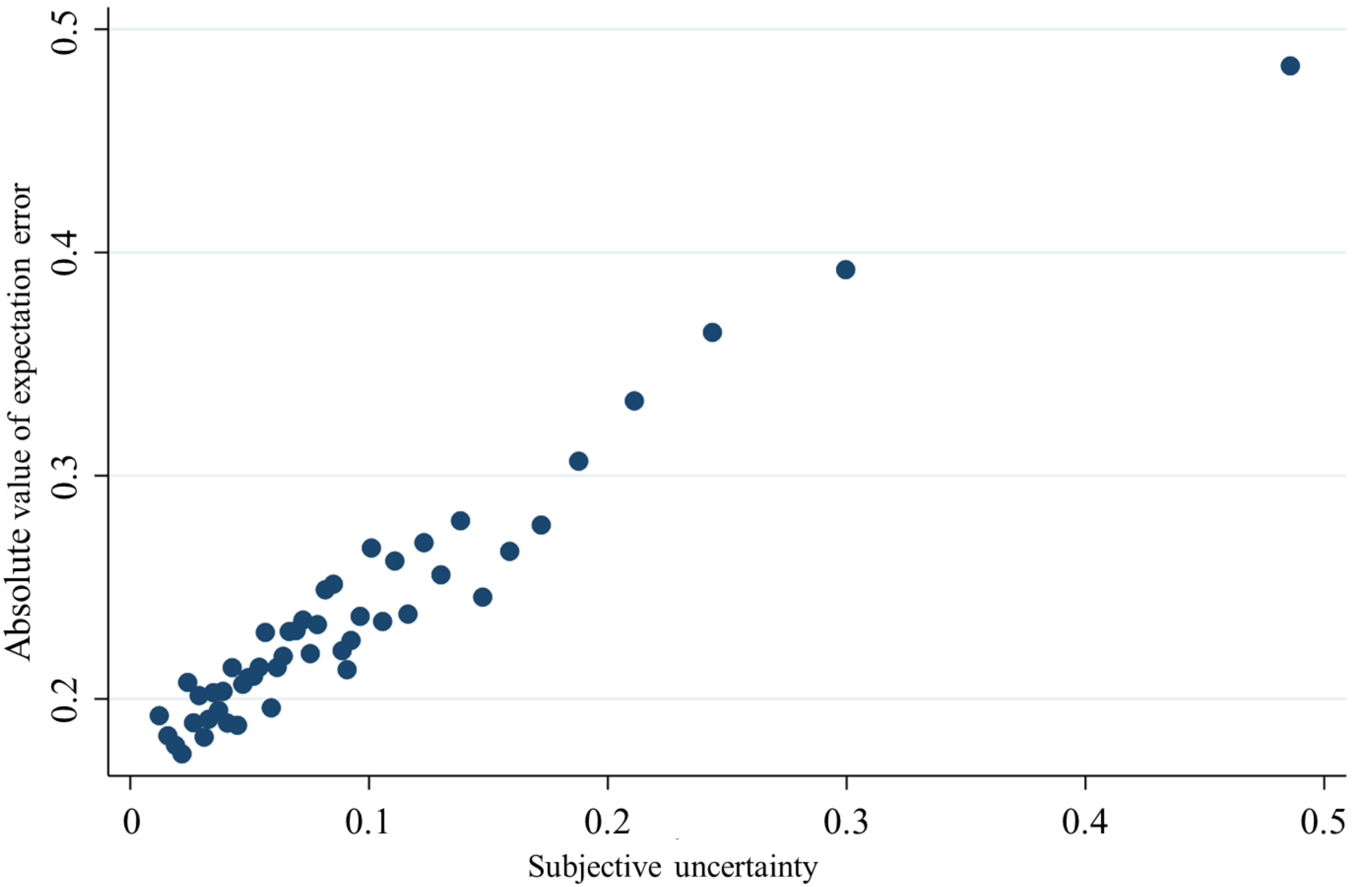
2017 scenarios, from lowest to highest	Approximate dollar value of shipments in 2017			Percentage likelihood (values in this column should sum to 100)
	$Bil.	Mil.	Thou.	
LOWEST				%
LOW				%
MEDIUM				%
HIGH				%
HIGHEST				%
			Total	100 %

Figure 2: Sales growth forecasts are strongly predictive of actual growth.



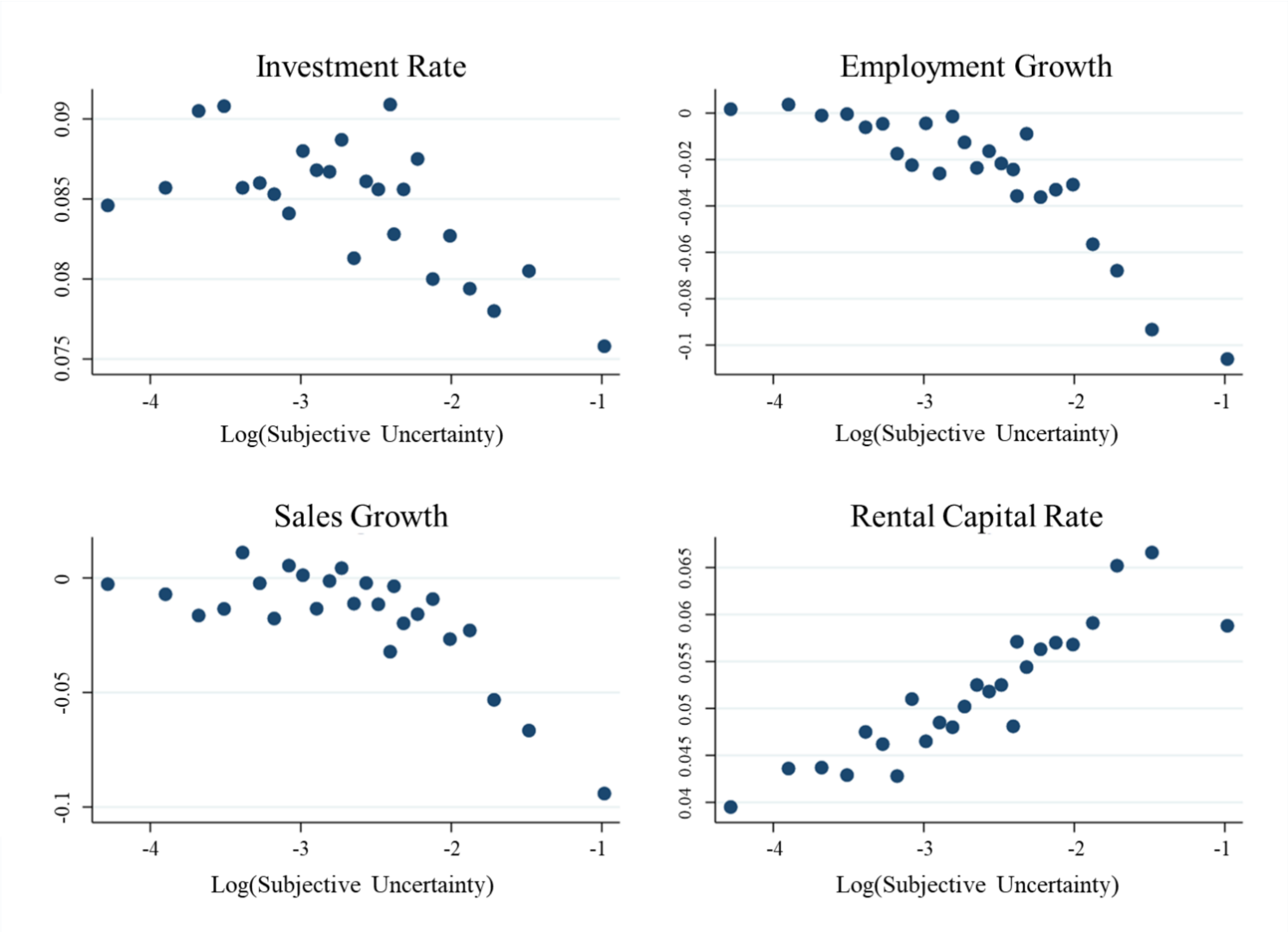
Notes: The calculated expected growth rate is the growth of the expected value of forecast 2017 shipments over the value of 2015 shipments reported on the MOPS. The calculated realized growth rate is the growth of 2017 shipments as reported on the 2017 CMF over 2015 shipments as reported on the 2015 ASM.

Figure 3: Sales uncertainty is strongly predictive of forecast errors.



Notes: The 2017 expectation errors are calculated as the difference between realized and expected growth rates of sales, where the realized and expected growth rates are calculated as in Figure 2. Subjective uncertainty is the standard deviation of the reported subjective distribution of sales growth from MOPS 2015.

Figure 4: Uncertainty exhibits strong negative relationships with investment, employment and sales growth, and a positive relationship with rental capital.



Notes: Subjective uncertainty is the standard deviation of the reported subjective distribution of sales growth from MOPS 2015. The investment rate is (capital expenditure in 2016)/(capital stock in 2015), employment and sales growth are measured as growth between 2015 and 2017 using the ASM and CMF, and rental capital rate is (capital rental in 2016)/(capital stock in 2015).