Manufacturing Uncertainty: Building Uncertainty Measures from Firm-Level Surveys*

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Abstract

This paper calculates three monthly measures of business uncertainty using information from the Institute of Supply Management's monthly purchasing managers survey. The three measures of uncertainty–while sourcing from the same microdata–differ in their methodology and relationship to some of the well-known measures of uncertainty. We calculate three ISM uncertainty metrics: One metric is based on free-from text provided by survey respondents and mirrors Baker et al. (2016). The other two are more novel and are based on intertemporal consistency of survey responses and the dispersion of firm-level responses to survey questions. All three measures are additions to the extant uncertainty metrics and are shown to be related to measures of economic activity.

JEL codes: C1, E17, O14

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1 Introduction

Uncertainty has always been an important component in understanding the current and future states of the economy for businesses, households, and policymakers. Recently, measuring economic uncertainty leapt to the forefront of both academic research and policy making in the wake of the Great Financial Crisis. There are multiple metrics that capture uncertainty, such as the volatility indexes derived from options, measures captured from textual data such as newspapers, or subjective probability distributions extracted from business surveys.

This paper calculates three monthly measures of business uncertainty using microdata from the Institute of Supply Management's (ISM) monthly purchasing managers survey. The ISM conducts a survey of purchasing managers from a sample of manufacturing firms in the United States that provides high-beta information for the national economy. The publicly available data primarily takes the form of diffusion indexes for a particular month. Recently the microdata–particularly the free form text–has been leveraged to examine the link between production and the sentiment calculated using natural language processing techniques (see Cajner et al. (2026)).

The three measures of uncertainty–while sourcing from the same microdata–differ in their methodology and relationship to some of the well-known measures of uncertainty. We calculate three ISM uncertainty metrics: One metric is based on free-from text provided by survey respondents and mirrors Baker et al. (2016). We find this measure, which is sourced from parsimonious free-form survey responses from manufacturing firms, mirrors metrics used in the literature.

The other two measures are slightly more novel. Given the ISM data is primarily diffusion index related–and that we have access to the underlying microdata–the statistical properties of diffusion indexes, somewhat adjacent to a binomial distribution, should provide us with a variance to each monthly reading. The variance speaks to the distribution of responses, naturally, and should also provide a metric related to the overall level of business uncertainty.

The third measure is an index based on intertemporal consistency of survey responses over time. Here we employ frequent changes in survey responses as a proxy for uncertainty. For instance, if a business changes whether new orders, increase, then decrease, then stay the same within three months we take that series of responses as an indicator for uncertainty.

All three measures are novel additions to the uncertainty literature and the goal is this paper is to not only provide evidence that the three measures of uncertainty exhibit peaks and troughs that align with periods of relatively high and low uncertainty, but can be related to measures of economic activity. Ideally, the uncertainty measures will provide a unique

signal about the future state of the economy.

2 Data

2.1 ISM Data

The primary data for this study comes from the Institute for Supply Management (ISM). Each month, ISM conducts a survey of purchasing managers from a sample of manufacturing firms in the United States.[1] Diffusion indexes based on the responses (described below) are published very rapidly, and are closely watched by markets. As highlighted in Bok et al. (2018), not only does such survey data provide important signal about the state of the economy, but the ISM data in particular provides the "earliest available information for the national economy on any given quarter". In addition, the ISM data have a long backhistory, which is conducive to time-series modeling.[2] The timeliness and relevance of the data motivates our exploration of the free-response text.

The ISM survey includes a series of questions about the respondents' operations, including their production levels, new orders, backlog, employment, supplier delivery times, input inventories, exports, and imports. These questions have a categorical response where the purchasing managers specify whether these metrics have increased, decreased, or stayed the same between last month and the current month. The categorical responses are aggregated into publicly-released diffusion indexes, discussed more below. In addition to the categorical response, purchasing managers can provide further explanation in accompanying text boxes. There are free response questions accompanying nearly every categorical question, asking for the reason for the response. In addition there is a "General Remarks" field at the beginning, where the respondent can put any general remarks they wish. Ten to twelve of these text responses are featured in the ISM's data release to provide context for the diffusion indexes, but otherwise they are not released publicly.

The dataset we analyze covers firm-month observations from November 2001 to January 2020. Most recently, the sample covers roughly 350 responses per month. The dark-shaded area of Figure 1 shows the percentage of firms in the sample with text responses over time. The figure illustrates that the majority of respondents provide text in addition to their quantitative survey answers. The black line in Figure 1 presents the average word count over the sample period. The word counts range from 10 to 33 words on average per month.

[1] ISM also surveys non-manufacturing firms and hospitals separately.

[2] ISM series extend back to 1948, but most statistical analyses use data that starts in 1972.

The mean word count appears to fluctuate over the business cycle and jumps dramatically in 2018. The sudden increase in word count in 2018 is mostly due to heightened tensions surrounding trade policy at the time.

Table 1 provides a summary of the text responses. Nearly 49 percent of the general remarks sections contain text, while the next most common sections containing text are those related to employment, production, and new orders. The last row shows statistics for all the text fields concatenated together: 69 percent of firm-month observations have any text at all, and the text is about 17 words long on average. The average word count is highest for the General Remarks section, with an average of 8 words used in these responses. When considering only those responses that contain text, the average word count for the General Remarks section increases to 16 words.

The ISM diffusion indexes are aggregations of the categorical response questions in the survey. For example, the production diffusion index is a weighted average of the responses to the production question (paraphrasing, "Is production higher/the same/lower than last month?"), with the "Higher" responses getting weight 100, "Same" responses getting weight 50, and "Lower" responses getting weight 0. The formula for the diffusion index in period t, with N_t total firms responding is shown in equation (1):

$$D_t = \frac{1}{N_t} \sum_{i=1}^{N} \left[100 \cdot \mathbf{1}\{\text{Response } i \text{ is "Higher"}\} + 50 \cdot \mathbf{1}\{\text{Response } i \text{ is "Same"}\} \right] \quad (1)$$

These diffusion indexes have values between 0 and 100, with 0 indicating that all respondents say things are worse and 100 indicating that all respondents say things are better.[3] [4] ISM publishes indexes for each question, as well as a "PMI Composite", which is an equally-weighted average of the diffusion indexes for new orders, production, employment, supplier deliveries, and inventories.

2.2 Manufacturing Production Data

Turning from the ISM survey data, we use several time series in our impulse response exercises. The primary target of interest is manufacturing production as published by the

[3] The responses are "better", "same", or "worse" for the new orders question, production, and new export orders. For employment, inventories, prices, and imports the responses are "higher", "same", and "lower". For backlogs the choices are "greater", "same", and "less".

[4] Note that this is identical to an index with weights of -1/0/1 on negative/neutral/positive responses, respectively, then recentered at 50 and scaled to run between 0 and 100. We use the (perhaps more intuitive) -1/0/1 weighting when dealing with the text data.

Federal Reserve Board.[5] A time series of manufacturing and total industrial production can be found in figure 2. Industrial production is an index of real production with a long time series (more than 100 years), consistent industries over time, and exists at the monthly frequency. Moreover, the goods economy, in general, tends to be highly cyclical. As a result, IP is an ideal input and target target for nowcasting and forecasting frameworks.

3 Measuring Uncertainty

Our goal is to extract useful information on economic uncertainty from the ISM survey responses. As noted, the standard free-form textual responses are somewhat parsimonious, so non-textual means of measuring uncertainty would complement the text-based approaches. To that end, in addition to generating the standard Baker et al. (2016) measure of economic policy uncertainty we derive two additional measures. Given we are working with the micro-data underlying diffusion indexes, a measure we term "confidence uncertainty" is based upon the statistical properties of diffusion indices and is the standard error of a diffusion index at a given point in time. We also calculate an uncertainty metric based upon the changes in survey responses over time, which we call "consistency."

3.1 Text Based Approach: ISM Policy Uncertainty

The text-based approach to measuring Economic Policy Uncertainty requires little introduction. Baker et al. (2016) pioneered this approach by counting articles that contain terms from categories pertaining to uncertainty, the economy, and policy. That is, the authors count of articles that contain a trio of the terms: "uncertainty" or "uncertain"; "economic" or "economy"; and one of the following policy terms: "Congress," "deficit," "Federal Reserve," "legislation," "regulation," or "White House."[6]

We follow a similar approach on the ISM free-form text responses from 2001 until 2019. That is, we take the count of survey responses that cite any of the policy or uncertainty words. Those responses are taken as a fraction of overall survey response and scaled to range between zero and a hundred.

The resultant index can be found in figure **??**. Interestingly, the ISM policy uncertainty index does not vary much prior to the Great Financial Crisis (GFC) and the concomitant

[5] See https://www.federalreserve.gov/releases/g17/ for more information

[6] The Economic Policy Uncertainty Indexes for various countries can be found at https://www.policyuncertainty.com/

recession, aside from a spike related to the second gulf war. Afterwards, there are spikes related to the Euro Crisis and several of domestic fiscal disputes, including the debt ceiling, fiscal cliff, and government shutdown. After 2017 the overall level of uncertainty rises with the transition to a new administration and several trade-related disputes.

Another way to view the ISM Policy Uncertainty index is through a comparison with the US Monthly EPU Index that is based on frequency counts of articles. Both the the ISM Policy Uncertainty and the EPU can be found in figure 3.

Importantly, both indexes have many of the same policy uncertainty peaks and the increase in the overall level of uncertainty towards the end of the displayed series. Not surprisingly, both series are highly correlated with a correlation coefficient of 0.57. This result is of particular value, as the ISM textual responses are orders of magnitude less text and context as opposed to the corpus of newspapers aggregated for the EPU index. Moreover, the ISM Policy Uncertainty Index measured here is also reflective of only the manufacturing sector. There are some differences, as well, such as the lack of as much movement prior to the GFC in the ISM Policy Uncertainty index. There were also substantially larger jumps in n the EPU index at the time of Brexit in June of 2016 and in November of 2016 at the time of the election of Donald Trump.

3.2 Uncertainty Based on the Variance of a Diffusion Index: Diffusion Dispersion

We now present an innovative means of estimating uncertainty based upon the statistical properties of a diffusion index, seen in equation (1).[7] The statistical property of interest we will be employing is the variance of the diffusion index. Recall, the diffusion index measures the aggregation of a survey's categorical responses.

In order to see how this variance is calculated, we need to define the proportion of survey respondents reporting an increase $p^u = \frac{n^u}{n}$, the proportion reporting a decrease $p^d = \frac{n^d}{n}$, and the proportion that indicate no change (or stayed the same) $p^s = \frac{n^s}{n}$. We are abstracting from time variation in these ratios, but for each month t we will have a variance estimate of the form.

[7]For a great exposition on the use of a diffusion index and the statistical properties employed here, see Pinto and Waddell (2022).

$$sigma_t = \frac{1}{N_t}\left[1 - p^s - D^2\right] \tag{2}$$

Equation (2) uses the diffusion index, D defined in (1) and p^s the proportion of respondents that indicate no change. Not surprisingly, the variance decreases as the sample size increases and also is equal to zero if all survey responses report "same" or there is an equal number of reporters indicating both "higher" and "lower." We call this metric "Diffusion Dispersion."

The resultant diffusion dispersion time series for new orders be found in figure 4. Of note, the diffusion index variance has high frequency movements and a longer term trends. Several of the high-frequency moves stand out, such as the seeming consensus prior to the GFC and the jump in diffusion variance at the time of Lehman Brothers liquidation. Of the longer term trend in this measure we see a gradual upward movement during the second half of the 2000s and a downward trend that reversed itself in 2019.

As mentioned earlier, the ISM collects survey information on nine different questions of interest. Two of which are directly related to international trade. The survey collects information to compile a diffusion index on imports and on new export orders. The trade-related diffusion dispersion indexes provide an interesting contrast to the TPU of Bok et al. (2018). Figure 6 plots export and import diffusion dispersion and TPU. The ISM measures move up substantially prior to the Great Financial Crisis, while the Bok et al. (2018) TPU moves sideways. More recently, the trade related shocks during the trade disputes in 2018 and thereafter seem to only barely push up the two ISM related indexes prior to COVID, but Bok et al. (2018) TPU jumps pretty notably at the time. The diffusion dispersion indexes for these two series will be leveraged further below in the empirical section.

3.3 Uncertainty Based on intertemporal inconsistency

Our final metric of uncertainty is based on the intertemporal consistency of ISM survey responses. That is, we attempt to use frequent changes in current activity as a proxy for uncertainty. Say, for example, a purchasing manager from the firm Zorin Industries reports whether or not the company's production has increased, decreased, or stayed the same. Changing the response to production each month for several months in a row could indicate a rapidly changing economic environment, changes in expectations, and/or inadequate production/input smoothing, all of which could be considered a refection of uncertainty.

Over the 18 year time period for which our data sample covers, an individual ISM survey respondent reports in the panel for an average of about 7 years with many firms in the sample for the entire time period. At any given point in time an individual survey response changes with probability .5. Given this "consistency" over time, we count the fraction of respondents that change their determination three times or more in 4 consecutive months. Over the entire sample period we find that this happens in about 17 percent of total observations. For any given time period t we calculate this as a proportion and transform the ratio into a 12-month moving average.

A plot of the outcome indecision index can be found in figure 5. There have been only five instances where the index surpasses 20 percent. That includes the runup to the Gulf War, prior to the Great financial Crisis, during Euro Crisis and the fiscal disputes prior to 2015. Importantly, the measure was moving upward in advance of COVID, which is mostly consistent with our other measures that indicate an overall slowing in the economy was in train and the first trade war of 2018.

3.4 Composite Indexes (to be completed)

So far the five measures of uncertainty are only calculated using the survey-level information on new orders and the entire corpus of free-form text. Additional metrics will be created for the responses of each series in the ISM, with a particular focus on the series the PMI is composed of (new orders, production, employment, suppliers' delivery performance, and inventories). From these composites a weighted average from overall uncertainty will be formulated. To be sure, non PMI related uncertainty measures will be calculated and estimated as well, including supplier deliveries. We will also explore seasonality within the aforementioned indexes.

4 Preliminary Empirical Results

With the three ISM uncertainty metrics in hand (text based, intertemporal consistency, and diffusion dispersion), this paper generates several permutations of the indexes and performs empirical tests to gauge their effectiveness in conveying information about economic factors.

We will compare our measures of uncertainty to the ubiquitous uncertainty measures used for policy and research purposes. Specifically, we will relate our metrics to the Economic Policy Uncertainty index Baker et al. (2016) , the VIX, Trade Policy Uncertainty Caldara et al. (2020), and the Atlanta Fed's Survey of Business Uncertainty Altig et al. (2022).

In addition, we will be investigating how innovations in our uncertainty metrics related to aggregate and manufacturing investment, output, and employment.

Before turning to more formal analysis, we report a correlation matrix with our variables of interest in table 3. The table contains the ISM-derived uncertainty indexes, the Economic Policy Uncertainty Index (BBD PU), TPU, and the VIX. In addition, we include growth in both employment and output for the manufacturing sector.

Several aspects of the matrix stand out. First, three general ISM derived metrics of uncertainty are not highly correlated. Indeed, the diffusion dispersion indexes are negatively correlated with the ISM policy uncertainty. Importantly, all three of the diffusion dispersion indexes are highly correlated, implying that uncertainty with respect to trade is related to diffusion dispersion, as well.

Second, the three extant measures of uncertainty are not necessarily all correlated with the ISM-derived indexes. Each of the diffusion dispersion indexes are highly correlated with with the VIX, but negatively correlated with the BBD TPU. The ISM policy uncertainty has a correlation coefficient of at about .4 with BBD PU.

Thirdly, each of the ISM-derived uncertainty measures are negatively correlated with manufacturing production. By contrast, and surprisingly, the employment metric is positively correlated with ISM policy uncertainty and outcome indecision, while negatively related to the diffusion dispersion measures. It should be noted that over the horizon of interest, changes in manufacturing employment is positively correlated with changes in manufacturing production.

Lastly, when comparing the smoothed and unsmoothed versions of outcome indecision, we find that that the 12 month moving average has higher correlations across all variables, indicating that the short horizon outcome indecision is somewhat volatile and noisy when calculated at the one-month horizon. We now turn to more formal regression framework to analyze correlations.

4.1 Regression Analysis

We relate the ISM measures to the BBD PU, TPU, and the VIX uncertainty measures through a basic linear regression framework. The specification can be found below and will regress each of the three extant uncertainty measures on the three ISM uncertainty measures.

$$Uncert_t = \alpha + \beta_1 ISMuncert_t + \delta x_t + \epsilon_t \tag{3}$$

As a result, there will be three separate talbes, one for each of BBD PU, TPU, and the VIX. In equation 3, $Uncert_t$ is BBD PU, VIX, or TPU measures of uncertainty, $ISMuncert_t$ is the ISM uncertainty measures, and x_t is control variables for month t.[8]

The results can be found in tables 4 through 6. The first three columns of each table run the target of interest uncertainty measure against the text based, intertemporal consistency, and diffusion dispersion ISM based uncertainty measures individually. The fourth column performs a horse race by including all three ISM-derived measures in the same specification.

Table 4 contains the results for the VIX measure. The results in table 4 indicate that of the individual measures, only the diffusion dispersion is correlated with the VIX, as seen in the third column. In the horse race specification, we find the ISM text based policy measure is also weakly significant. Recall that the VIX is related to financial market volatility, as it is the expectation of near term volatility conveyed by stock index option prices. As a result, while the VIX is related to uncertainty, it might be more financial market focused.[9]

Table **??** contains the results for the BBD PU measure. Perhaps it is not surprising that the ISM PU measure is significantly related, as both are text based uncertainty measures sourcing their corpus of terms similarly. Similar to our previous table, the diffusion dispersion measure if also significantly related to the BBD PU measure.

Table 6 contains the results for the trade policy uncertainty measures. Recall the trade policy uncertainty measure is a text-based measure, similar in spirit to the BBD PU, but with textual terms related to trade policy, such as tariffs, import duty import barrier, and dumping. In table 6 we also include the export and import diffusion dispersion measures described above.

The table 6 results indicate that ISM policy uncertainty is significantly and positively related to TPU across all specifications. Interestingly, while significant, both outcome indecision and diffusion dispersion are negatively related to the TPU metric. For the two trade-related diffusion dispersion measures, only the import metric is significant and it too has a negative sign with respect to the aggregate TPU measure.

With the ISM related measures showing statistically meaningful relationships with the extant measures of uncertainty, we now turn to an analysis that attempts to measure the impact of a shock to firms ISM-based measures of uncertainty and real activity.

[8]The current version of the results does not include control variables.

[9]See Bekaert et al. (2013) for a discussion of the VIX as it relates to uncertainty, finding that the VIX might be more related to time-varying risk-aversion rather than economic uncertainty.

4.2 Impulse Response Functions

Measures of uncertainty have been shown to be strongly counter cyclical. One method, as seen in Baker et al. (2016) and reviewed in Cascaldi-Garcia et al. (2023) is to utilize VAR models to exploit the time series variation and capture the dynamic relationships. As a result, we analyze the contemporaneous, high-frequency comovement of IP and uncertainty using local projections following Jordà (2005).

Local projections involves estimating a series of separate regressions for each forecast horizon h, where the outcome variable of interest is regressed on the contemporaneous shock and relevant controls.

Specifically, for each h, we estimate the following equation:

$$IP_{t+h} - IP_{t-1} = \alpha + \tau_t + \sum_{l=0}^{L} \beta_l^h \Delta Uncert_{t-l} + \sum_{l=1}^{L} \gamma_l \Delta IP_{i,t-l} + x_t + \epsilon_{t+h} \tag{4}$$

where IP_{t-1} is Manufacturing Industrial Production, $Uncert_t$ is BBD, VIX, TPU, and the ISM measures of uncertainty, and x_t is control variables for month t, including the ISM indices for new orders, PMI, and inventories.

The results for the local projection impulse responses can be found in Figure 7. We first start with tried and true measures of uncertainty found in the existing literatures. As seen in Figure 7, a shock to the Baker et al. (2016) and the VIX measures of uncertainty both lead to negative and significant movements in manufacturing production. Moving to the ISM-derived measures, a shock to the outcome indecision and diffusion dispersion measures also lead to negative movements in production in the industrial sector.

4.3 Uncertainty and Investment

The previous results suggest that increases in uncertainty lead to declines in manufacturing. In this subsection, we provide evidence that this relationship is mediated by an investment channel whereby uncertainty propagates to real activity via declines in capital expenditures. We collect quarterly data on capital expenditure from Compustat for all manufacturing firms (NAICS 31-33). In figure 8, we show the outcome indecision measure alongside the year over year growth for total manufacturing capex across all manufacturing firms. While capital expenditure growth exhibits considerable volatility, periods of declining uncertainty are generally accompanied by increases in capex, and vice versa. To test this mechanism in a more rigorous setting, we regress one-period ahead firm-quarter level capex growth on cur-

rent uncertainty in table 7. Our baseline specification controls for firm size, manufacturing PMI, new orders, and manufacturing growth. To account for unobserved heterogeneity, we progressively introduce firm-year and firm-calendar quarter fixed effects. Our results suggest that manufacturing uncertainty has a significant and negative effect on firm's capital expenditure decisions. The consistently negative coefficient on our uncertainty measure across all specifications suggests that the relationship is robust to both observed and unobserved factors.

This evidence is consistent with real options theory, where heightened uncertainty increases the option value of delaying investment projects and leads to firms scaling back their manufacturing activity (Bloom, 2009). To further buttress this mechanism, in future versions of the paper we will relate responses from the ISM's semi-annual survey, which explicitly asks firms about their imminent capital expenditure plans , with our measures of uncertainty. Furthermore, we will apply generative AI techniques to the ISM respondent's comments to assess how sentiment around capex planning evolves during periods of hightened uncertainty.

5 Conclusion

The results included in this paper are entirely preliminary. With that said, the findings are promising, as we have evaluated new and useful data for calculating uncertainty from text covering the operations of manufacturers. Importantly, the parsimony in the ISM text relative to some of the public sources of uncertainty is an important contribution of this data source.

Our results find that the ISM-derived uncertainty measures not only are significantly related to some of the already popularized measures of uncertainty, but are dynamically related to measures of economic activity.

There are multiple directions in which this paper will be extended. Looking further into the ISM-derived TPU measures, aggregating the PMI sub-aggregates to create higher-levels of uncertainty, and working with firm level investment decisions are all part of our research agenda with this new and enlightening data source.

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Tables

Table 1: Survey Summary Statistics

Field	(1) Fraction W/ Text	(2) Mean Word Count	(3) Mean Word Count Cond. on Text
General Remarks	0.49	7.86	15.94
Production	0.27	1.42	5.27
New Orders	0.27	1.45	5.41
Backlog	0.19	1.13	6.05
Employment	0.52	1.29	6.21
Supplier Speed	0.12	0.89	7.23
Input Inventories	0.23	1.51	6.50
Exports	0.10	0.59	5.88
Imports	0.12	0.79	6.43
All Text (Appended)	0.69	16.92	24.42

Notes: Summary statistics derived from the ISM survey. Column (1) reports the fraction of firm-month observations containing any text. Column (2) shows the mean word count across all firm-month observations, while column (3) shows the mean word count of only those responses containing any text. Each row corresponds to one of the various question types on the ISM survey.

Table 2: Summary Statistics

	(1) Mean	(2) Std. Dev.	(3) Min	(4) Median	(5) Max
Uncertainty Measures					
EPU	153.2	86.2	44.8	134.4	724.94
VIX	19.5	8.1	10.1	17.4	62.67
TPU	75.1	119.4	11.3	33.7	1151.36
ISM Uncertainty Measures					
ISM Policy Uncertainty	3.9	3.2	0.0	3.0	20.40
Unsmoothed Outcome Indecision (New Orders)	0.2	0.0	0.1	0.2	0.25
Unsmoothed Outcome Indecision (Production)	0.2	0.0	0.1	0.2	0.24
Outcome Indecision (New Orders)	0.2	0.0	0.1	0.2	0.21
Outcome Indecision (Production)	0.2	0.0	0.1	0.2	0.19
Diffusion Dispersion (New Orders)	0.0	0.0	0.0	0.0	0.01
Diffusion Dispersion (Production)	0.0	0.0	0.0	0.0	0.00
Diffusion Dispersion (Exports)	0.0	0.0	0.0	0.0	0.00
Diffusion Dispersion (Imports)	0.0	0.0	0.0	0.0	0.00
Macro Variables					
IP Growth$_t$	0.0	1.3	-15.2	0.0	7.74
Emp Growth$_t$	-0.1	0.7	-10.3	0.0	2.93
ISM PMI$_t$	52.8	4.9	34.5	52.8	63.80
ISM NewOrders$_t$	54.9	7.3	25.9	55.5	71.30
ISM Inventories$_t$	48.3	4.2	33.5	48.7	56.80

Notes: Summary statistics for the variables used in the analysis. The data ranges from October 2001 through February 2026.

Table 3: Correlation Matrix

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
(1) EPU	1.00																
(2) VIX	0.36	1.00															
(3) TPU	0.71	-0.04	1.00														
(4) ISM Policy Uncertainty	0.78	0.07	0.78	1.00													
(5) Unsmoothed Outcome Indecision (New Orders)	0.11	-0.02	0.06	0.16	1.00												
(6) Unsmoothed Outcome Indecision (Production)	0.11	-0.01	-0.02	0.14	0.57	1.00											
(7) Outcome Indecision (New Orders)	0.08	0.02	-0.06	0.08	0.44	0.26	1.00										
(8) Outcome Indecision (Production)	0.15	-0.04	-0.11	0.16	0.23	0.42	0.67	1.00									
(9) Diffusion Dispersion (New Orders)	-0.24	0.31	-0.27	-0.30	0.17	0.03	0.18	-0.09	1.00								
(10) Diffusion Dispersion (Production)	-0.24	0.35	-0.30	-0.32	0.14	0.03	0.19	-0.08	0.96	1.00							
(11) Diffusion Dispersion (Exports)	-0.10	0.41	-0.19	-0.16	0.14	0.05	0.25	0.04	0.87	0.87	1.00						
(12) Diffusion Dispersion (Imports)	-0.14	0.46	-0.22	-0.19	0.13	0.05	0.23	0.01	0.85	0.88	0.87	1.00					
(13) IP Growth$_t$	-0.06	-0.26	0.02	-0.10	-0.07	-0.04	-0.11	-0.05	-0.04	-0.05	-0.10	-0.12	1.00				
(14) Emp Growth$_t$	-0.05	-0.34	0.04	-0.05	-0.07	-0.02	-0.08	0.08	-0.21	-0.22	-0.24	-0.25	0.79	1.00			
(15) ISM PMI$_t$	-0.23	-0.46	-0.11	-0.19	-0.12	0.06	-0.15	0.10	-0.24	-0.22	-0.29	-0.26	0.29	0.40	1.00		
(16) ISM NewOrders$_t$	-0.32	-0.46	-0.16	-0.29	-0.11	0.01	-0.13	-0.01	-0.14	-0.12	-0.23	-0.20	0.36	0.38	0.91	1.00	
(17) ISM Inventories$_t$	0.07	-0.36	0.10	0.16	-0.04	0.11	-0.06	0.26	-0.38	-0.39	-0.34	-0.33	0.08	0.31	0.62	0.32	1.00

Notes: Correlation Matrix for the variables used in the analysis. The data ranges from October 2001 through February of 2026. Variables are numbered (1)-(17) in column headers for space. All correlations rounded to 2 decimal places.

Table 4: VIX as Dependent Variable

	(1)	(2)	(3)	(4)	(5)	(6)
ISM Policy Uncertainty	0.073					0.230***
	(0.061)					(0.062)
Outcome Indecision (New Orders)		0.018				-0.088
		(0.081)				(0.079)
Outcome Indecision (Production)			-0.036			0.011
			(0.065)			(0.065)
Diffusion Disp. (New Orders)				0.315***		-0.416*
				(0.064)		(0.242)
Diffusion Disp. (Production)					0.355***	0.838***
					(0.066)	(0.248)
Constant	-0.002	-0.013	-0.013	-0.002	-0.002	-0.012
	(0.059)	(0.060)	(0.060)	(0.056)	(0.055)	(0.054)
Observations	292	286	286	292	292	286
R^2	0.005	0.000	0.001	0.099	0.126	0.182
Adj. R^2	0.002	-0.003	-0.002	0.096	0.123	0.167

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: EPU as Dependent Variable

	(1)	(2)	(3)	(4)	(5)	(6)
ISM Policy Uncertainty	0.778***					0.787***
	(0.066)					(0.073)
Outcome Indecision (New Orders)		0.081				0.011
		(0.055)				(0.048)
Outcome Indecision (Production)			0.152***			0.016
			(0.057)			(0.051)
Diffusion Disp. (New Orders)				-0.235***		-0.132
				(0.039)		(0.125)
Diffusion Disp. (Production)					-0.241***	0.127
					(0.043)	(0.121)
Constant	0.000	0.002	0.002	0.000	0.000	-0.011
	(0.037)	(0.060)	(0.059)	(0.057)	(0.057)	(0.037)
Observations	292	286	286	292	292	286
R^2	0.603	0.006	0.023	0.055	0.058	0.618
Adj. R^2	0.602	0.003	0.019	0.052	0.055	0.611

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: TPU as Dependent Variable

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ISM Policy Uncertainty	0.786***						0.810***
	(0.103)						(0.104)
Outcome Indecision (New Orders)		-0.060					0.101**
		(0.044)					(0.039)
Outcome Indecision (Production)			-0.107**				-0.304***
			(0.046)				(0.043)
Diffusion Disp. (New Orders)				-0.268***			0.108
				(0.031)			(0.136)
Diffusion Disp. (Production)					-0.299***		-0.140
					(0.038)		(0.150)
Diffusion Disp. (Exports)						-0.017	-0.001
						(0.065)	(0.071)
Diffusion Disp. (Imports)						-0.204***	-0.055
						(0.074)	(0.088)
Constant	0.001	0.008	0.008	0.001	0.001	0.001	-0.006
	(0.036)	(0.060)	(0.060)	(0.057)	(0.056)	(0.057)	(0.033)
Observations	292	286	286	292	292	292	286
R^2	0.615	0.004	0.011	0.072	0.089	0.048	0.682
Adj. R^2	0.614	0.000	0.008	0.068	0.086	0.041	0.674

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Regression Results: TPU

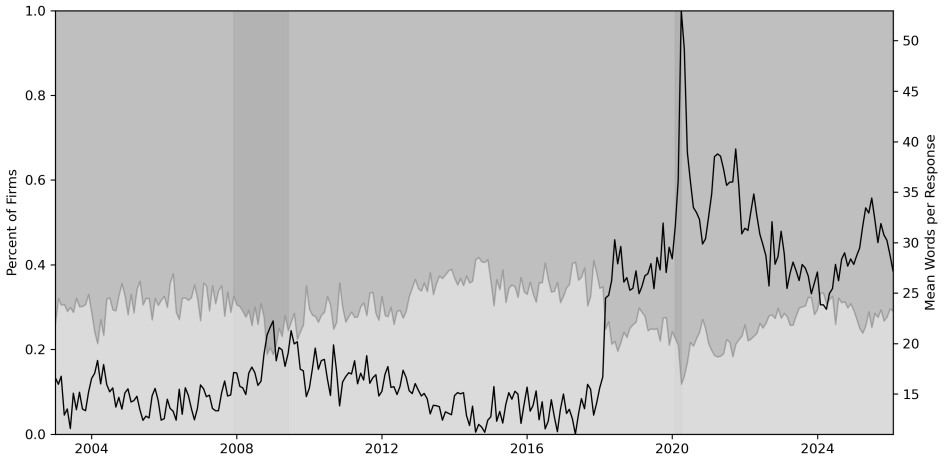
	(1)	(2)	(3)	(4)
	YoY Capex Growth(t+1)			
$OutcomeIndecision_t$	-1.422***	-1.438***	-0.307**	-1.482***
	(0.3020)	(0.3150)	(0.1510)	(0.3330)
$Log(Assets)_{f,t}$	-0.0378***	-0.0510***	-0.0123***	-0.0398***
	(0.0054)	(0.0068)	(0.0026)	(0.0067)
$ISMPMI_t$	0.0136***	0.0151***	0.0174***	0.0128***
	(0.0018)	(0.0019)	(0.0013)	(0.0020)
$ISMNewOrders_t$	-0.00794***	-0.00914***	-0.00932***	-0.00819***
	(0.0010)	(0.0011)	(0.0008)	(0.0012)
$IndustrialProductionGrowth_t$	0.0277***	0.0307***	0.0465***	0.0372***
	(0.0036)	(0.0039)	(0.0035)	(0.0041)
Observations	145098	142655	146694	115980
R-squared	0.403	0.428	0.057	0.43
Firm*Year FE	Y	Y	N	Y
Firm*Quarter of Year FE	N	Y	Y	Y
Sample	All	All	All	US Only Firms

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figures

Figure 1: ISM Survey Responses



Notes: This figure shows the percentage of firms and the word counts for the ISM survey responses. [Left Axis] The light (dark) grey region shows the percent of firms that provided empty (non-empty) responses on their monthly response. [Right Axis] The black line shows the mean number of words per response across all respondents for a given month.

Figure 2: Manufacturing and Total Industrial Production

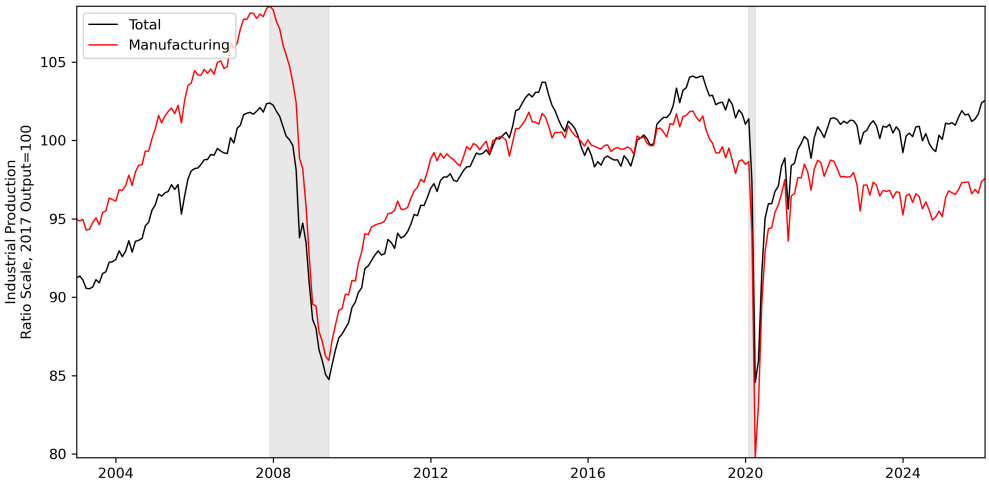
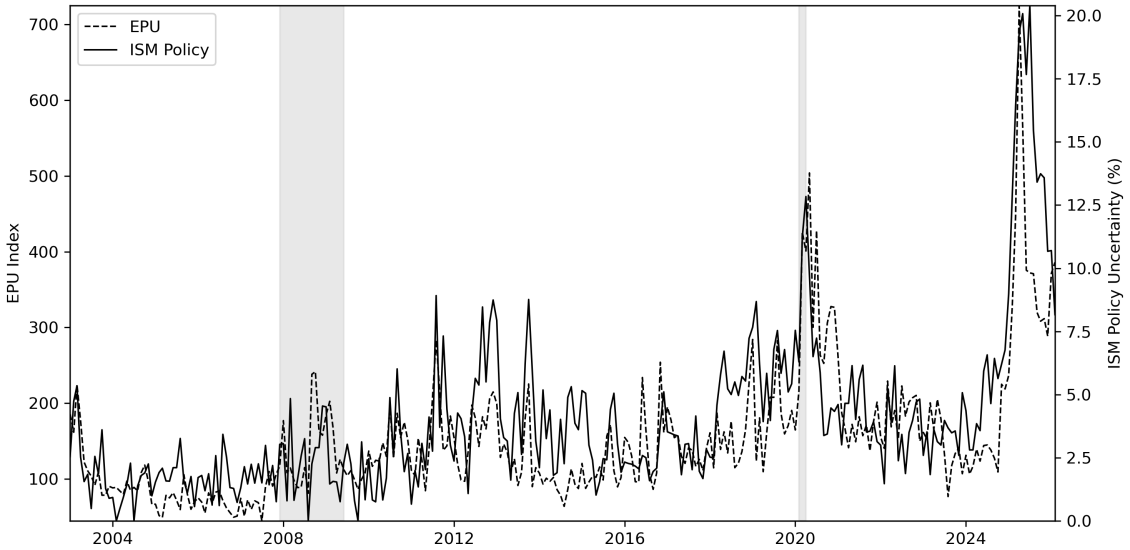
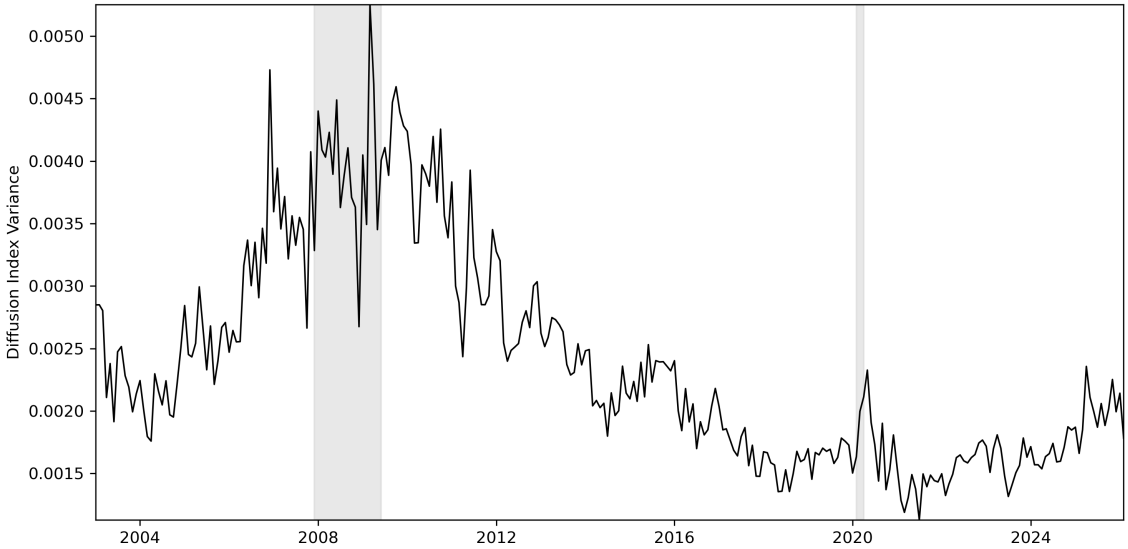


Figure 3: ISM Policy Uncertainty and EPU Indexes



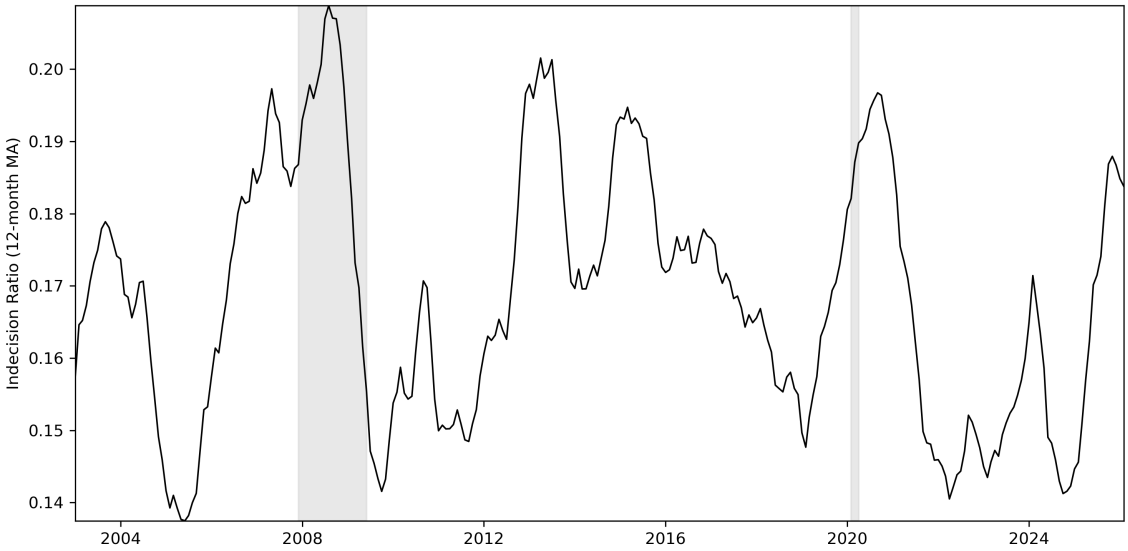
Notes: This figure shows The Economic Policy Uncertainty Index from Baker et al. (2016) for the United States and the text-based ISM Policy Uncertainty Index.

Figure 4: Diffusion Index Variance



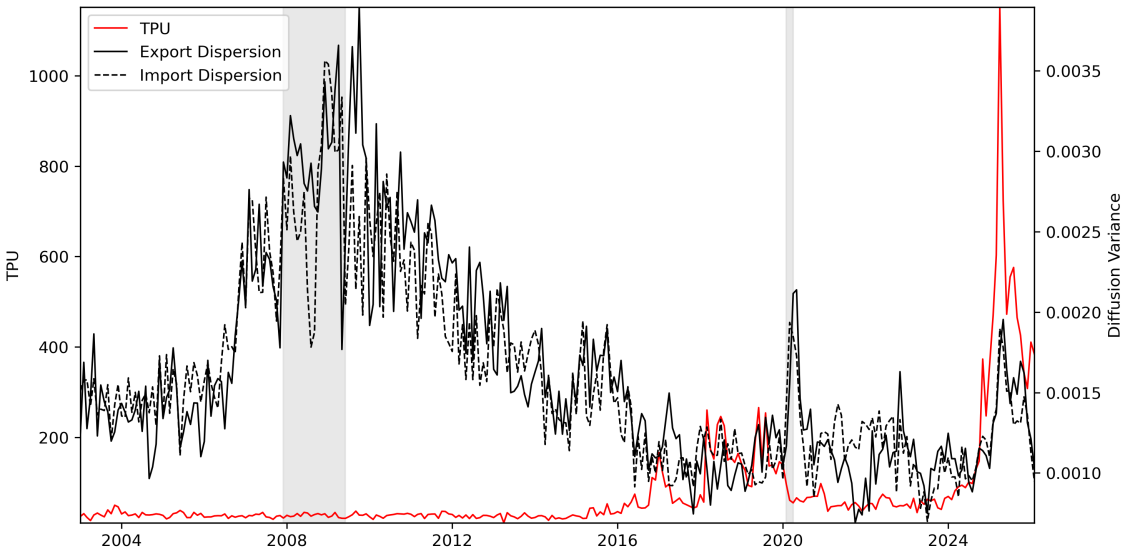
Notes: This figure shows the unscaled variance of the ISM New Orders Index.

Figure 5: Outcome Indecision Uncertainty Index



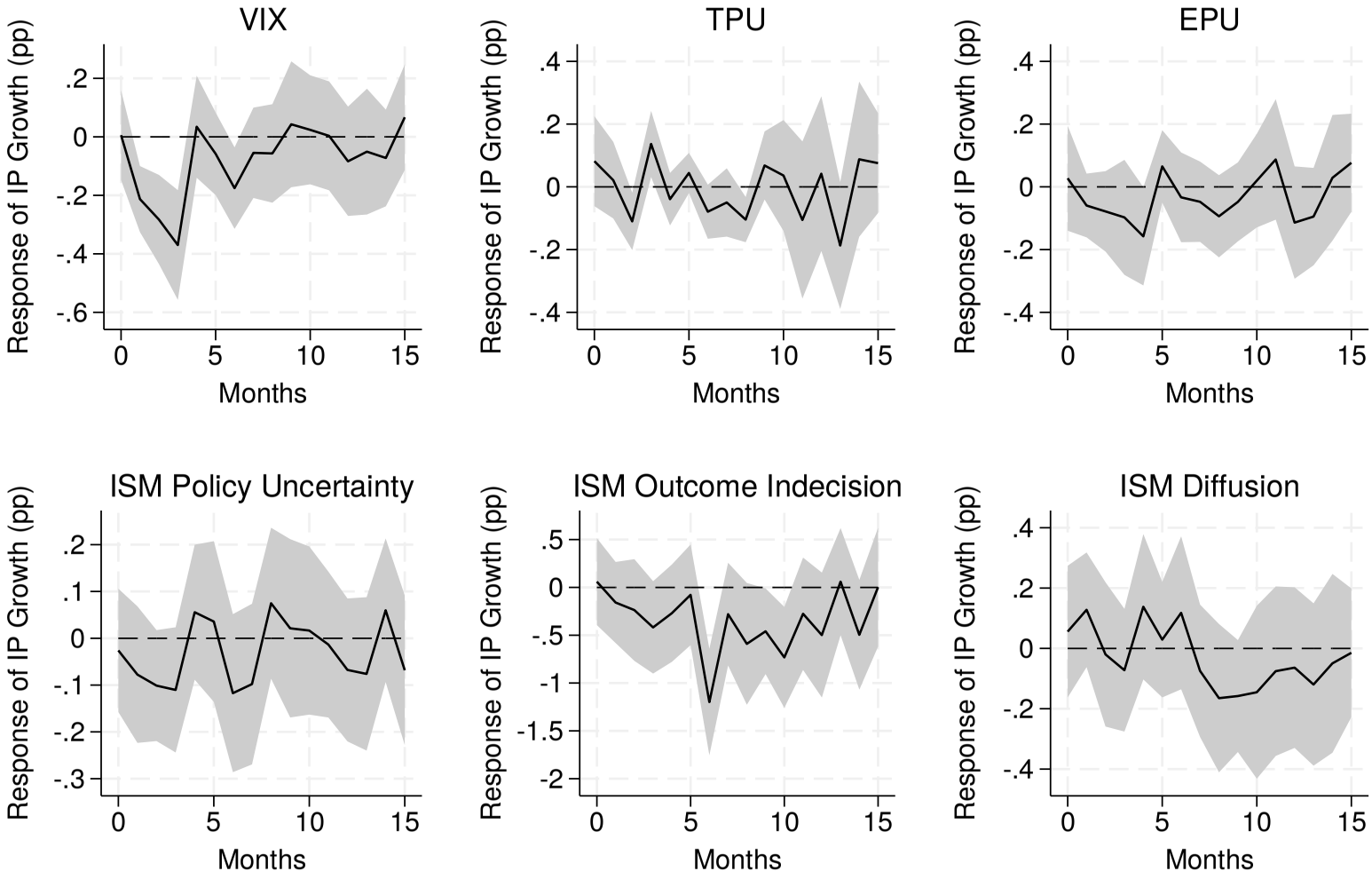
Notes: This figure shows the 12-month moving average of our Outcome Indecision Uncertainty Index.

Figure 6: Outcome Indecision Uncertainty Index



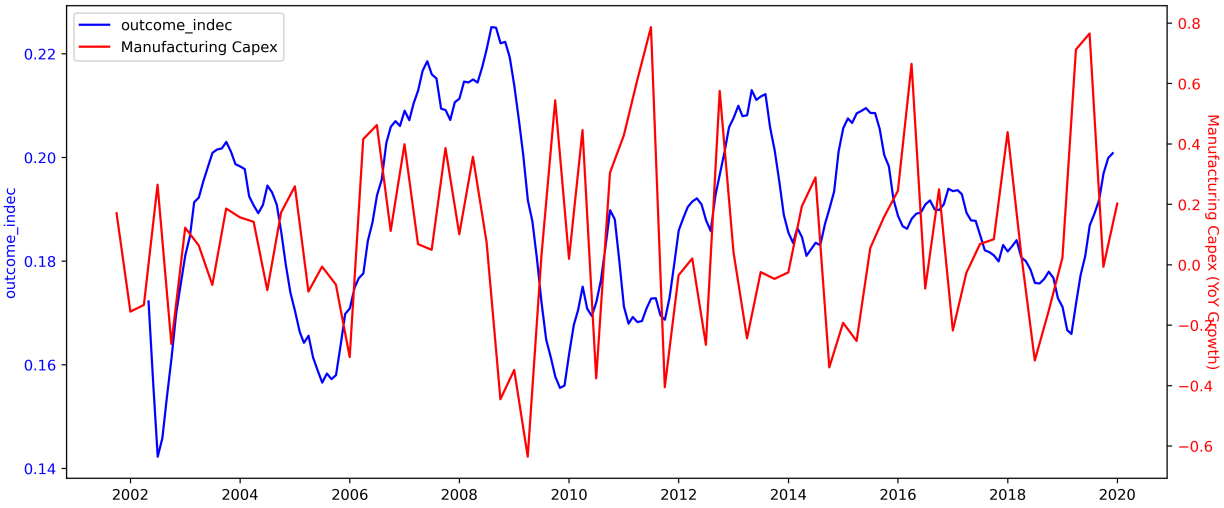
Notes: This figure shows the two ISM trade uncertanty metrics alongside the TPU index.

Figure 7: Impulse response functions: Local Projection



Notes: The data excludes COVID years (2020-2021). The impulse response functions include controls for the ISM PMI, inventories, and new orders indices.

Figure 8: Outcome Indecision vs Total Manufacturing Capital Expenditure



Notes: This figure shows outcome indecision (blue) and year-over-year capex growth across all manufacturing firms, NAICS 31-33, in Compustat (red).