Expectation dispersion, uncertainty, and the reaction to news*

Benjamin Born, Jonas Dovern, Zeno Enders

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Abstract

Key macroeconomic indicator releases are closely monitored by financial markets. We examine the impact of expectation dispersion and economic uncertainty on the stock market's reaction to these indicators. We find that the strength of the financial market response to news decreases with the preceding dispersion in expectations about the indicator value. Higher uncertainty, in contrast, increases the response. We rationalize our findings in a model of imperfect information. In the model, dispersion results from a perceived weak link between macroeconomic indicators and fundamentals that reduces the informational content of indicators, while fundamental uncertainty makes their informational content more valuable.

Keywords: Expectation dispersion, uncertainty, macroeconomic news, stock market, event study, forecaster dispersion
JEL-Codes: E44, G12, G14

*Born: Frankfurt School of Finance & Management, CEPR, CESifo, and ifo Institute, b.born@fs.de, Dovern: Friedrich-Alexander-Universität Erlangen-Nürnberg and CESifo, jonas.dovern@fau.de, Enders: Heidelberg University and CESifo, zeno.enders@uni-heidelberg.de. We thank Christian Conrad, Alexander Glas, and various seminar audiences for useful comments and discussions. All remaining errors are ours. This research has received financial support by the German Science Foundation (DFG) under Priority Program 1859.

1 Introduction

A cursory glance at the financial news media suggests that stock markets eagerly await releases of macroeconomic indicators, such as initial jobless claims or inflation, and that stock prices are highly sensitive to macroeconomic news, i.e., surprises in these indicators. This general perception is supported by a large academic literature showing that releases of macroeconomic information indeed move financial markets (e.g., Andersen et al., 2007; Beechey and Wright, 2009; Fleming and Remolona, 1999; Law et al., 2020; Scotti, 2016, among many others). Importantly, the link between macroeconomic news and asset prices, i.e., the news effect, has been shown to vary across states of the economy, e.g., booms and recessions (Boyd et al., 2005; Gilbert, 2011; McQueen and Roley, 1993), and to depend on the informational content of individual indicators (Ehrmann and Sondermann, 2012; Gilbert et al., 2017).

This paper contributes to the existing literature by demonstrating that the news effect on the stock market can be influenced by two time-varying factors: (forecaster) expectation dispersion and aggregate economic uncertainty. Interestingly, these factors affect the stock market reaction in opposite ways. This finding is new and underscores that uncertainty and dispersion are not only different concepts that are imperfectly correlated (e.g., Giordani and Söderlind, 2003; Lahiri and Sheng, 2010; Zarnowitz and Lambros, 1987) but can actually have opposite effects on the stock market. Additionally, the paper investigates how these effects are affected by the state of the business cycle and the monetary policy stance.

We use a high-frequency dataset that includes $1,671$ releases across six major macroeconomic indicators for the US economy. For each indicator release, we collect the prior individual forecasts of a panel of professional forecasters from Bloomberg and compute both the dispersion of forecasts across the panel members, i.e., their disagreement, and the difference between the median forecast and the actual realization of the indicator, i.e., the news content of the release. To our knowledge, we are the first to exploit the cross-section of the Bloomberg survey data on macroeconomic news announcements. Across indicators, there is notable heterogeneity in average dispersion. There is also considerable variation in dispersion over time. Regarding uncertainty, we employ the real-uncertainty proxy of Ludvigson et al. (2021) in our baseline specification. While average dispersion is correlated with the uncertainty proxy, the correlation coefficient is only about 0.5.

To determine the stock market response to news releases, we conduct an event study that looks at the change in S&P 500 futures prices in a narrow window around the indicator release. Specifically, we regress these returns on the news variable, forecast dispersion, the uncertainty measure, as well as—and most importantly for our investigation—interaction terms between news and dispersion and news and uncertainty, respectively.

Consistently for all indicators, we find that—holding uncertainty constant—an increase in expectation dispersion leads to weaker news effects on stock market returns. These effects matter quantitatively: the effect of a one-standard-deviation surprise in, e.g., non-farm payrolls is halved if dispersion is one standard deviation above its mean. On the other hand, holding dispersion constant, macroeconomic news that materialize in more uncertain times generate a stronger stock market response than those hitting in tranquil times. We then proceed and investigate whether there are non-linear, potentially state-dependent effects of uncertainty and dispersion on the reaction to news. Here, we only find (statistically) weak evidence that our finding of opposing effects from uncertainty and dispersion on the stock market's reaction to news is stronger during recessions and phases of monetary tightening.

Our findings are robust to the type and frequency of uncertainty proxy—e.g., economic policy uncertainty (Baker et al., 2016) or the daily real-activity uncertainty proxy of Scotti (2016)—or the length of the event window. Interestingly, this does not hold true once we replace the baseline real uncertainty measure with monetary policy uncertainty (Husted et al., 2020). Here, we find that an increase in the latter counteracts the positive effect of favorable news on stock markets, in particular for those indicators that are deemed important for monetary policy decisions. This might be driven by, e.g., speculations about future rate hikes in time of high monetary policy uncertainty (see also Kurov and Stan, 2018).

Formally, we interpret dispersion and uncertainty as representing the perceived information content of a specific indicator and the economic value of the contained information, respectively. We illustrate this by setting up a stylized theoretical model of imperfect information to sketch out how uncertainty and dispersion influence financial-market participants' reaction to macroeconomic news. In the model, the current fundamentals of the economy are unobserved, such that financial-market participants have to rely on occasional releases of observable indicators that are linked to the underlying fundamentals. The strength of this link, i.e., the informational content of these indicators, is time-varying. Agents receive private signals about the tightness of the link, which are dispersed in case of a low informational content. In a nutshell, a large dispersion signals a higher noise content of a specific indicator, which also reduces its informational content regarding fundamentals. The market reaction to the subsequent indicator release is thus muted. That is, if financial analysts differ strongly in their belief about an upcoming indicator release, this release is unlikely to move markets much.

Uncertainty about current fundamentals, on the other hand, relates to the volatility of shocks that move fundamentals. Information becomes more valuable in times of high uncertainty, such that markets react stronger to indicator releases for a given perceived link between these indicators and fundamentals. As a result, the model predicts that uncertainty about fundamentals and dispersed expectations of forecasters have opposite effects on the strength of the market reaction to news—just as we find in the data.[1]

The remainder of this paper is organized as follows: Section 2 introduces the dataset and describes the empirical modeling approach. Section 3 then contains the main empirical results from our event study and Section 4 checks their robustness. We rationalize our empirical findings with the help of a stylized model in Section 5. Finally, Section 6 concludes.

[1] Note that our finding about the different effects of monetary policy uncertainty does not stand in contrast to our explanation regarding the effects of uncertainty and expectation dispersion, given that the theoretical model makes predictions about the effects of uncertainty about *real* variables.

2 Data and empirical model

In this section, we first introduce the dataset and collect a number of stylized facts. We then set up and discuss the empirical model.

2.1 Dataset

We focus on six major macroeconomic indicators. The first four are those that Law et al. (2020) found to induce the largest and most significant financial market movements: the change in non-farm payrolls (abbreviated as CNP), initial jobless claims (IJC), the ISM manufacturing index (ISM), and the Conference Board consumer confidence index (CCI). In addition, we consider GDP growth (GDP) and the inflation rate based on the consumer price index (CPI). These indicators vary in release frequency between weekly (IJC) and quarterly (GDP) and are released at 8:30 am, except for ISM and CCI, which are released at 10:00 am. Individual forecasts by professional forecasters covering these indicators come from Bloomberg. Forecasters can submit or update their predictions up to the night before the official indicator release, so these forecasts are likely to contain all available information at the time of the indicator release. To obtain reliable estimates of dispersion, we consider only data releases for which ten or more corresponding forecasts are available. The earliest indicator release that fulfills this criterion takes place in August 1997; there are eight of those releases before 1999. Our sample ends in March 2015. Overall, the number of data releases covered across time and indicators is $1,671$, with an average number of panelists of 51.4.[2]

Given the individual forecast of forecaster j for an indicator i at time t, $\hat{y}^i_{j,t}$, we define dispersion as the cross-sectional standard deviation of forecasts:

$$D^i_t = \left[\frac{1}{N^i_t} \sum_{j=1}^{N^i_t} \left(\hat{y}^i_{j,t} - \frac{1}{N^i_t} \sum_{j=1}^{N^i_t} \hat{y}^i_{j,t} \right)^2 \right]^{\frac{1}{2}} , \tag{1}$$

[2]Note that our dataset is unbalanced as the frequency at which indicators are released and the start dates for indicator availability vary. See Table A.1 in the appendix for details.

where N_t^i is the number of forecasts submitted for indicator i at time t.

In addition, we compute a (normalized) measure of macroeconomic news, $News_t^i$, by subtracting the median forecast from the published indicator value, y_t^i, and dividing by the standard deviation (across time) of this difference.

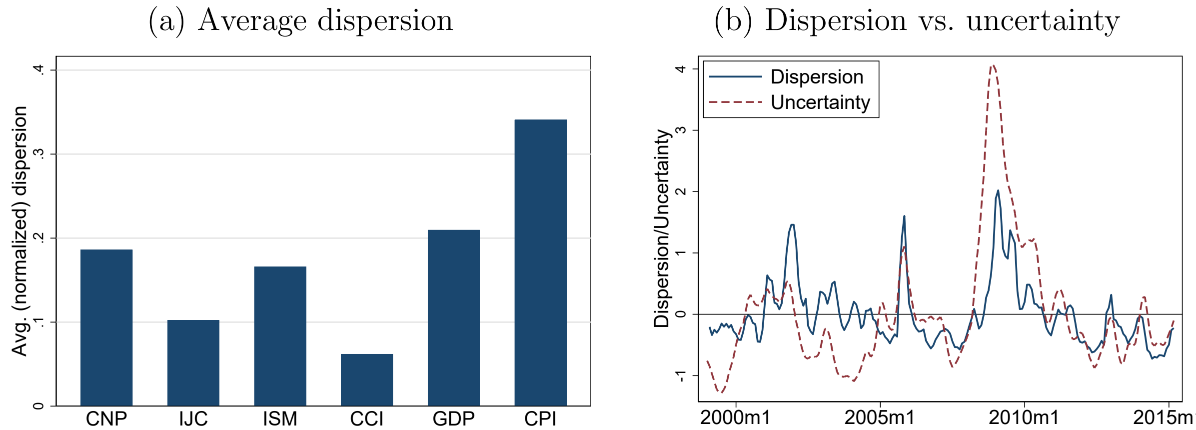
As measuring uncertainty directly is inherently difficult, we have to rely on proxies. For our baseline results, we use the real-uncertainty proxy of Ludvigson et al. (2021) to stay close to the uncertainty concept in the model of Section 5, which is uncertainty about the fundamental. Briefly speaking, the real-uncertainty measure of Ludvigson et al. (2021) is the common factor of the uncertainty connected to variables covering the real economy.[3]

For the stock market data, we use tick-by-tick prices of S&P 500 futures provided by TickData. We need to use futures data as most of the indicator releases are outside the trading hours of the New York Stock Exchange. We use equity data as equity prices can be expected to be influenced by most macroeconomic news.

To get a first sense of the forecast dispersion in our sample, Panel (a) of Figure 1 displays the average forecast dispersion for our six indicators, normalized by the standard deviation (across time) of the respective median forecast. Across indicators, there is notable heterogeneity in average dispersion. There is also considerable movement in dispersion over time, as the blue solid line in Panel (b) shows. Specifically, we plot the three-month moving average of monthly average dispersion across all indicators. It is also evident that dispersion is correlated with our baseline uncertainty measure; but the correlation is far from perfect (correlation coefficient of 0.504 for the monthly averages).

[3]We check the robustness of our results to the choice of the uncertainty proxy in Section 4. We also investigate whether the uncertainty of each of the macroeconomic indicators considered here comoves with this aggregate uncertainty. To this end, we estimate univariate stochastic volatility models for each indicator, where the conditional mean and variance follow AR(1) processes. We plot the posterior means of the estimated conditional variances against the Ludvigson et al. (2021) measure in Figure A.1 in the Appendix. Correlations are sizable, between 0.21 (CNP) and 0.57 (CPI).

Figure 1: Dispersion and uncertainty



Notes:: Panel (a): average forecast dispersion across indicators; Panel (b): dispersion (solid blue line) vs. uncertainty (dashed red line). Dispersion in Panel (a) normalized by the standard deviation (across time) of corresponding median forecasts.

2.2 Empirical model

We employ an event-study framework in which one event represents a point in time at which—potentially multiple—indicators are released. The dependent variable is the (percentage) change in futures prices between five minutes before the data release and five minutes afterwards, which we denote by $R_t^{\pm 5}$.[4] We regress these returns on the news variables, the forecast dispersion, D_t^i, the uncertainty measure, UNC_t, interaction terms between news and dispersions and news and uncertainty, respectively, and a set of control variables. Thus, our baseline regression, which we estimate by OLS, is given by

$$\begin{aligned} R_t^{\pm 5} &= \alpha + \sum_{i=1}^{I} \left(\beta_1^i News_t^i + \beta_2^i D_t^i + \beta_3^i News_t^i \times D_t^i \right) \\ &\quad + \beta_4 UNC_t + \sum_{i=1}^{I} \left(\beta_5^i News_t^i \times UNC_t \right) + \gamma' X_t + \varepsilon_t \ , \end{aligned} \tag{2}$$

where α is a constant, I is the number of indicators (six in our case), X_t includes the number of forecasters who submitted a forecast before a data release (to control for potential

[4]Our results are robust to the choice of the specific window size. For example, extending the length of the window before the event to 15 minutes and after the event to 30 minutes has only minor effects on our results (see the last column of Figure A.3 in the appendix).

systematic dropout behavior) and dummies for the months February to December (to control for potential seasonality), and ε_t is a zero mean i.i.d. error term.[5] Note that we run this regression for all indicators jointly. The setup hence follows Beechey and Wright (2009) in that it allows for the possibility of parallel indicator releases at time t. Those right-hand-side variables belonging to indicators not released at time t are set to zero.

In our baseline, UNC_t is a monthly measure of aggregate uncertainty in the real economy. In robustness checks, we also consider more granular measures that give us the aggregate uncertainty at the specific day before the event. Finally note that Equation (2) suffers from a slight abuse of notation for simplicity. It's easiest to think of t as denoting the event, i.e., the news release, and D_t^i and UNC_t being the corresponding dispersion and uncertainty measures "belonging" to that event. In practice, the dispersion of forecasts is observed the night before the release at the latest. With regard to our baseline monthly uncertainty measure, we use uncertainty of the month in which the event takes place.[6] For the daily uncertainty measures, we use the observation the day before the news release.

Given the estimates for the parameters β_1^i, β_3^i, and β_5^i, we can then analyze how strong the immediate news effect on future returns is for different levels of dispersion and uncertainty. Below, we present results that we compute by fixing the respective other variables at their sample means.

3 Results

Table 1 presents the results of the baseline regression (2). While we are ultimately interested in the interaction effects between news and dispersion on the one hand and news and uncertainty on the other hand, we focus for a moment on the direct—holding all other variables at their sample mean—effects of our macroeconomic news variable on stock returns. The first row of the table shows that these generally have the expected signs. For CNP, ISM,

[5] As a robustness check, we also calculate HAC standard errors and find that the results are not much different from those shown in Section 3.

[6] We verify in a robustness check that using the previous month's uncertainty does not change our results.

Table 1: News effects on stock returns depending on the levels of dispersion and uncertainty

	CNP	IJC	ISM	CCI	GDP	CPI
News	0.265***	-0.056***	0.129***	0.168***	0.119***	-0.095***
	(0.019)	(0.008)	(0.016)	(0.016)	(0.031)	(0.018)
Unc.			0.010			
			(0.007)			
Disp.	-0.018	-0.002	-0.015	0.024	0.046	0.019
	(0.017)	(0.008)	(0.016)	(0.017)	(0.035)	(0.017)
News × Unc.	0.136***	-0.026**	0.015	0.052***	0.075*	-0.049*
	(0.022)	(0.008)	(0.015)	(0.015)	(0.032)	(0.019)
News × Disp.	-0.082***	0.012*	-0.016	-0.034*	-0.046	0.049***
	(0.018)	(0.006)	(0.017)	(0.016)	(0.031)	(0.015)
Constant			0.008			
			(0.014)			
N			1,725			
R^2			0.230			
			Test of difference in interaction coefficients			
F-statistic	44.06	10.38	1.85	14.43	4.68	9.93
p-value	(0.00)	(0.00)	(0.17)	(0.00)	(0.03)	(0.00)

Notes: Results from a single regression. Not shown but included are month fixed effects and the number of forecasters who submitted a forecast before the respective data release.

CCI, and GDP, a positive forecast error, i.e., a realization larger than expected, constitutes good news and the stock market reacts with a significant increase. For IJC and CPI on the other hand, the stock market takes a positive forecast error as bad news (e.g., because of looming interest-rate hikes or production capacity constraints in the case of CPI) and falls significantly.[7]

The second and third row of Table 1 contain the coefficients on Uncertainty and Dispersion. Under the null of perfect information, the level of ex-ante forecast dispersion and

[7]Since we normalize macroeconomic news, the coefficients should be interpreted as the effect of an increase of news by one standard deviation. Take, e.g., the standard deviation of the news measure for GDP, which is 0.76 percentage points. The estimated coefficient implies that futures prices increase by 0.119 percent, on average, when forecasters underestimate a release of GDP growth by 0.76 percentage points.

uncertainty should not be correlated with the unpredictable change in stock prices. And that is exactly what we find, coefficients are insignificantly different from zero.[8]

The next rows contain the main coefficients of interest for our analysis, the interaction effects between news and uncertainty on the one hand and news and dispersion on the other hand. For all macroeconomic indicators, the sign of news interacted with uncertainty is opposite that of dispersion. Thus, forecast dispersion and uncertainty seem to have very different effects on the market reaction to news. The bottom panel of Table 1 provides test statistics and p-values for tests of equality of the slopes of the interaction effects. For five of the six indicators, the null of equality is rejected (ISM being the exception due to large standard errors).

We investigate this finding further in Figure 2. Specifically, we plot for each of the six indicators the marginal effects of news on S&P 500-futures returns for different levels of dispersion (blue solid line) and uncertainty (red dashed line). Here, dispersion and uncertainty both increase along the horizontal axis from left to right, while the vertical axis displays the marginal effects.[9] The shaded areas are the accompanying 90%-confidence intervals.

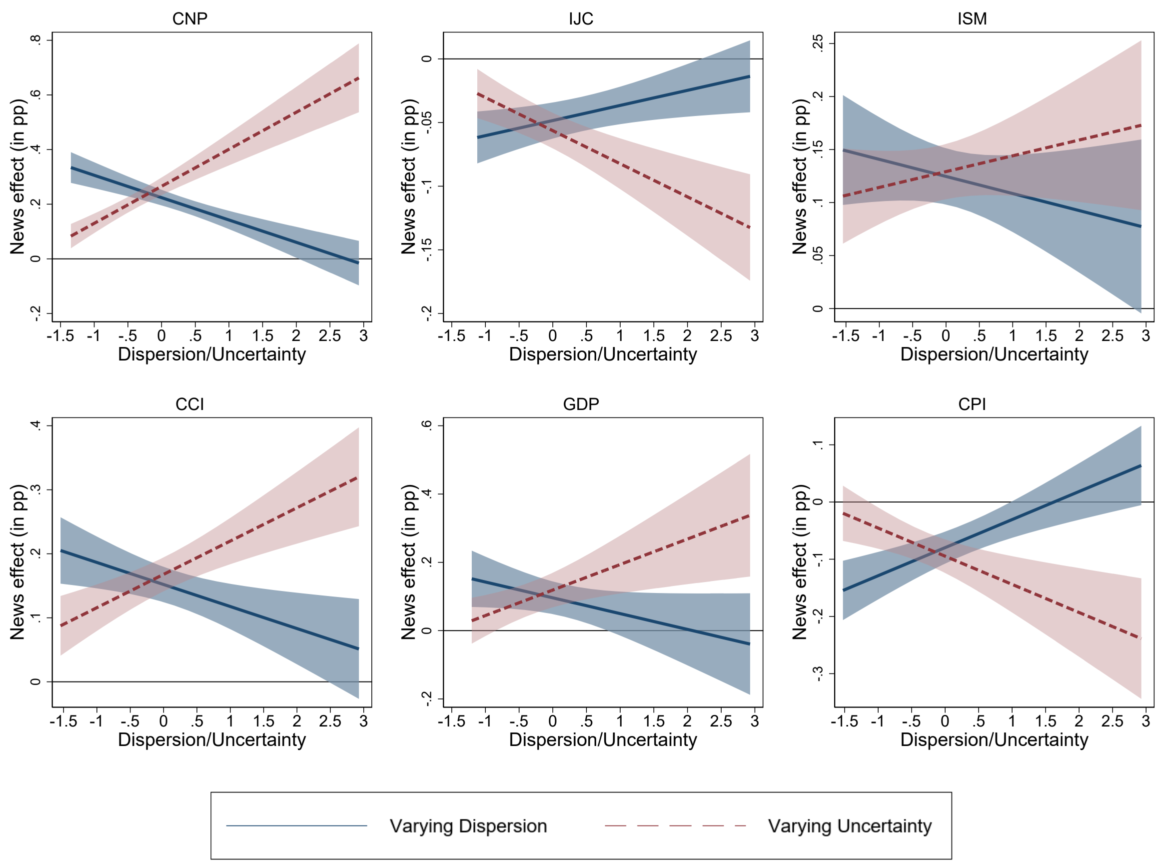
Focusing first on dispersion and holding uncertainty at its average level, we see that in all six panels the slope of the solid blue line is sloping towards the horizontal zero line with increasing dispersion. That is, news have a smaller effect on stock markets if forecasts about the indicator of interest were more dispersed beforehand. The effect can be sizable. If the dispersion of forecasts for, e.g., non-farm payrolls is one standard deviation above its mean, the effect of a one-standard-deviation surprise is halved.

Importantly, the picture flips when we look at uncertainty. For all indicators considered, the dashed red line diverges from the horizontal zero line for higher levels of uncertainty,

[8]This is also true for the coeffients on the month fixed effects and the number of survey participants contained in X_t (not shown here).

[9]Note that the x-axis range is asymmetric because in the data dispersion (and uncertainty) exhibits large positive spikes and is therefore not symmetrically distributed. Note also that the effect sizes are normalized to make them comparable across indicators and uncertainty measures in the robustness checks. In particular, we standardize news and dispersion for each indicator and all uncertainty measures by subtracting the sample mean and dividing by the sample standard deviation.

Figure 2: Effects of news on stock returns for varying levels of dispersion and uncertainty.



Notes: y-axis depicts marginal effects of news in p.p. for different levels of dispersion (blue solid line) and uncertainty (red dashed line); x-axis: "0" means dispersion/uncertainty is at its average level, "-1" ("1") indicates that it is one standard deviation below (above) its average level; shaded areas: 90%-confidence intervals. All other variables are fixed at their sample means. For additional information, see Footnote 9.

meaning that the stock market reaction is stronger if the macroeconomic news materializes in times of high uncertainty.

A natural question to ask is whether there are non-linear, potentially state-dependent effects of uncertainty and dispersion on the reaction to news. We investigate this in two dimensions. First, we use the business cycle dating published by the NBER to define a regime dummy that is 1 during recessions and 0 otherwise. Second, we define a dummy that is 1 during periods of monetary tightening and 0 otherwise; we define the start of a monetary tightening period by the date of the first increase of the Federal Reserve target rate in one cycle and the end by the date just before the first interest rate reduction. Figure A.2 in the

Table 2: Non-linear interactions

	CNP	IJC	ISM	CCI	GDP	CPI
			A) State of the business cycle			
	CNP	IJC	ISM	CCI	GDP	CPI
News × Unc.						
NBER==1	0.170***	-0.021*	0.002	0.063**	**0.327***	-0.094**
	(0.035)	(0.011)	(0.020)	(0.020)	(0.143)	(0.034)
NBER==0	0.131***	-0.036*	0.038	0.043	**-0.013**	-0.012
	(0.037)	(0.018)	(0.029)	(0.037)	(0.065)	(0.036)
News × Disp.						
NBER==1	**-0.172*****	0.013	-0.026	**-0.111*****	-0.271	0.073***
	(0.045)	(0.010)	(0.036)	(0.029)	(0.152)	(0.022)
NBER==0	**-0.069*****	0.013	-0.015	**-0.005**	-0.029	0.031
	(0.019)	(0.007)	(0.019)	(0.018)	(0.036)	(0.021)
			B) Stance of monetary policy			
	CNP	IJC	ISM	CCI	GDP	CPI
News × Unc.						
Mon.Pol.==1	**0.218*****	-0.068	**0.296*****	**0.274****	0.156*	-0.039
	(0.042)	(0.035)	(0.044)	(0.084)	(0.079)	(0.045)
Mon.Pol.==0	**0.107*****	-0.024**	**-0.022**	**0.041****	0.069	-0.049*
	(0.025)	(0.008)	(0.016)	(0.015)	(0.042)	(0.021)
News × Disp.						
Mon.Pol.==1	-0.097***	0.016	**-0.107****	-0.046	-0.049	0.057*
	(0.022)	(0.011)	(0.033)	(0.047)	(0.035)	(0.029)
Mon.Pol.==0	-0.065*	0.014*	**-0.012**	-0.049**	-0.051	0.047**
	(0.025)	(0.007)	(0.019)	(0.017)	(0.048)	(0.016)

Notes: Regressions for Panels A) and B) additionally include all regressors listed in Table 1. We use business cycle dating published by the NBER to define a regime dummy that is 1 during recessions and 0 otherwise. Second, we define a dummy that is 1 during periods of monetary tightening and 0 otherwise; we define the start of a monetary tightening period by the date of the first increase of the Federal Reserve target rate in one cycle and the end by the date just before the first interest rate reduction. Coefficients in bold face are significantly different from the corresponding coefficient in the other regime at the 5% level (using a 10% level leads to the same conclusion).

appendix shows the identified regimes. It's important to note that the two dimensions are distinct, e.g., recessions and monetary loosening periods do not overlap perfectly.

Table 2 presents the results from two separate regressions, with Panel A showing the results for recessions/non-recessions and Panel B showing the results for monetary tightenings/loosenings. We focus here on the regime dependence of the interaction terms but all other regressors from the baseline are still included in the regressions. The overall picture is mixed. While point estimates indicate that our finding of opposing effects from uncertainty and dispersion on the stock market effects of news are stronger in recessions (bold face), the majority of coefficients are not significantly different in the two regimes. This is also true when distinguishing along the monetary stance dimension. Here, estimates point towards a stronger distinction in phases of monetary tightening, but statistical power is again weak.

4 Robustness

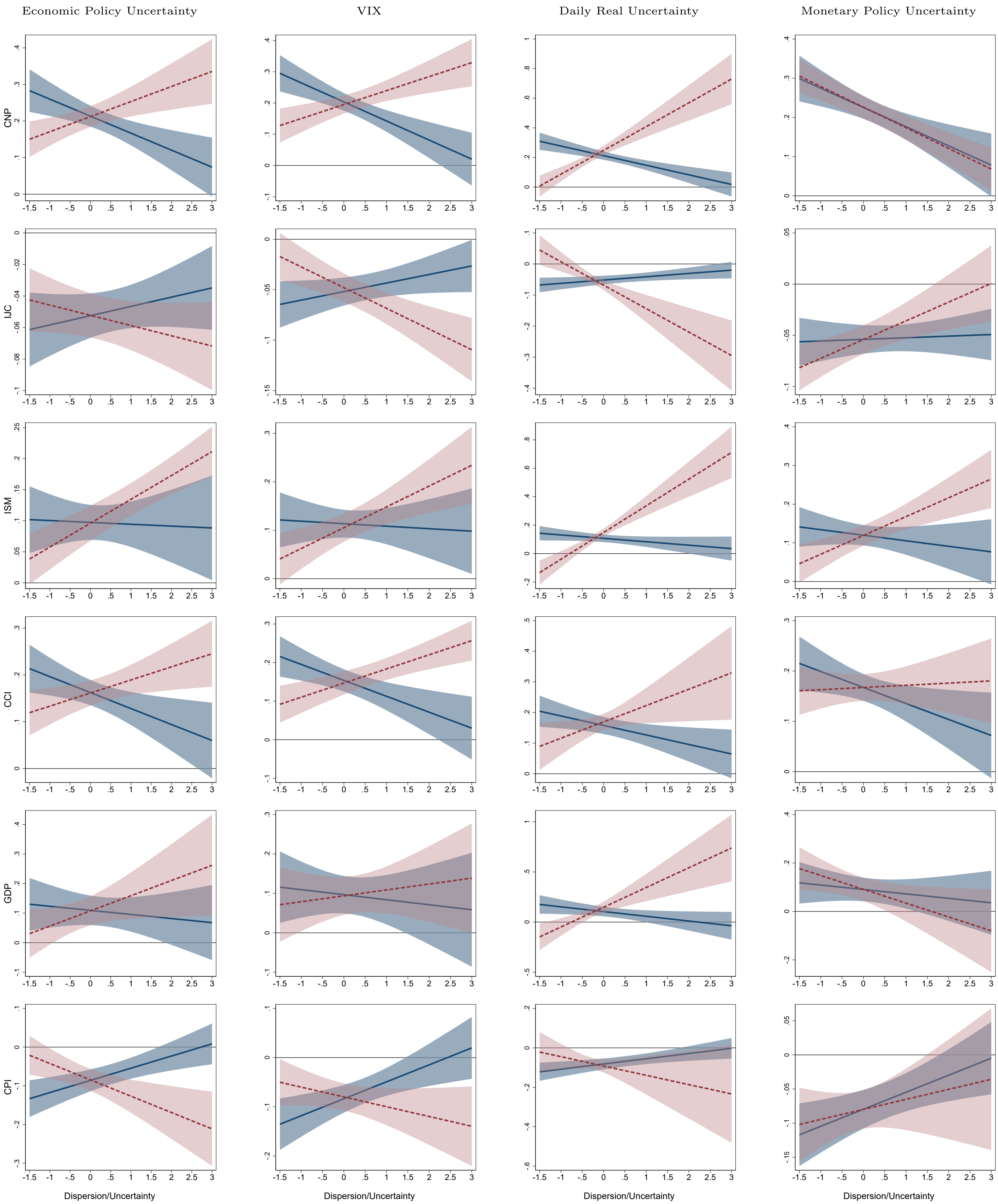
Given that measuring aggregate uncertainty is inherently difficult, we check the robustness of our results by considering a number of alternative proxies. The first two columns of Figure 3 show results equivalent to Figure 2 but with the economic policy uncertainty (EPU) measure of Baker et al. (2016) and the VIX, respectively, as the uncertainty proxy. These two proxies use very different approaches to measuring uncertainty. At its heart, EPU is based on the count of news articles that refer to the terms "economy, uncertainty and policy", while the VIX summarizes expected stock market volatility implied by options prices. In addition, both measures are available at daily frequency, which allows us to check whether using a monthly measure in the baseline is driving our results, e.g., the monthly uncertainty measure might be driven up by an event that happens later in the month after the releases of the economic indicators.[10] Overall, results look very similar, which is also underscored by the respective rows in Table 3.[11] While EPU and VIX are well-known and often-used uncertainty proxies, they do not measure *real* economic uncertainty. We, therefore, also consider the daily real uncertainty index constructed by Scotti (2016) which is computed as the weighted average of squared surprises from a set of data releases.[12] Results are shown in column 3 of Figure 3:

[10] With the daily uncertainty proxies, we use the previous day's level of uncertainty in Regression (2). We also conduct a robustness check in which we lag the baseline monthly uncertainty proxy to rule out contamination from events after the data release event. The third column of Figure A.3 in the Appendix shows that this has only minor effects on our results.

[11] The difference in slopes becomes insignificant for GDP-growth news. However, it is important to keep in mind that GDP numbers are only released at quarterly frequency and we, therefore, have considerably fewer events compared to the monthly or weekly releases of other indicators.

[12] The Scotti (2016) index is available starting in 2003 until the end of our sample. Since we have data releases starting in 1997, we use the baseline monthly real uncertainty index to prolong the uncertainty index for the first few years to keep the samples comparable.

Figure 3: Robustness checks varying the uncertainty proxy.



Notes: see Figure 2.

Table 3: Test of difference of slopes

	CNP	IJC	ISM	CCI	GDP	CPI
Economic policy uncertainty	19.44	5.44	18.64	7.40	2.35	8.93
	(0.00)	(0.02)	(0.00)	(0.01)	(0.13)	(0.00)
Implied volatility – VIX	19.10	10.16	8.92	16.64	0.43	6.04
	(0.00)	(0.00)	(0.00)	(0.00)	(0.51)	(0.01)
Daily real uncertainty	33.54	13.06	27.84	5.86	9.69	2.13
	(0.00)	(0.00)	(0.00)	(0.02)	(0.00)	(0.15)
Monetary policy uncertainty	0.03	3.03	7.89	1.70	1.17	0.25
	(0.85)	(0.08)	(0.00)	(0.19)	(0.28)	(0.62)

Notes: Test of difference in slopes for the interaction effects between news and dispersion and news and uncertainty. Test statistic with p-value in parentheses. Economic policy uncertainty: daily newspaper-based proxy (Baker et al., 2016); daily real uncertainty: daily proxy based on (squared) data-release surprises (Scotti, 2016); monetary policy uncertainty: monthly newspaper-based proxy (Husted et al., 2020).

again, they look very similar to the baseline and, except for inflation, the differences in slopes are significantly different from zero (Table 3, row 3).

In Figure A.3 in the appendix, we report results for additional uncertainty proxies. Using the macroeconomic uncertainty proxy of Jurado et al. (2015) or the financial uncertainty proxy of Ludvigson et al. (2021) does not change the overall picture. Both are very similar in construction to our baseline real uncertainty measure but cover somewhat different aspects of economic uncertainty—the financial uncertainty proxy focuses on a large set of financial time series while the macroeconomic uncertainty proxy covers both economic as well as financial time series.

The one uncertainty measure that yields a rather different picture is monetary policy uncertainty as measured by Husted et al. (2020), see the right column of Figure 3. In line with the findings of Kurov and Stan (2018), higher monetary policy uncertainty actually weakens the stock market response to macroeconomic news. This is arguably sensible if one considers that this variable explicitly measures uncertainty about the future interest rate. In times of monetary policy uncertainty, favorable news about the state of the economy may raise the odds of an interest-rate increase. This could lead to a stronger discounting of expected future dividends, counteracting the positive effects of the surprise.[13] The effect is particularly strong for indicators that are deemed to be important for monetary policy decisions, see IJC, GDP, and CPI, while ISM and CCI are less relevant in this context. Note, that the dampening effect of monetary policy uncertainty does not stand in contrast to our findings about the role of uncertainty and dispersion. Specifically, monetary policy uncertainty is only loosely connected to the concept of uncertainty about the fundamental as specified in our theoretical model of Section 5. It, therefore, might have a different but unrelated influence on the stock-market response to news.

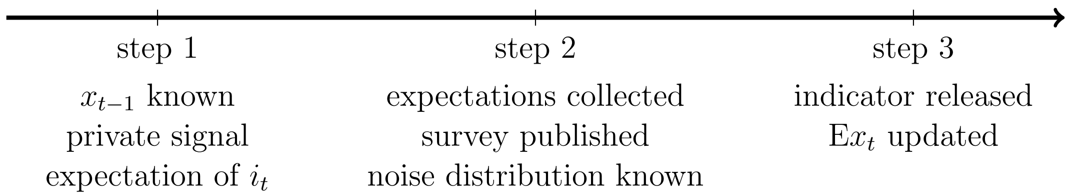
5 Model

In this section, we set up a stylized model that will rationalize our empirical findings on how uncertainty and dispersion influence financial-market participants' reaction to macroeconomic news. The model is deliberately kept as simple as possible, as its main purpose is to illustrate a link between certain characteristics of individual expectations and the information content of news. As we will show, the model matches our empirical findings in that it predicts that uncertainty about fundamentals and dispersed expectations of forecasters have opposite effects on the strength of the reaction of markets to news. In the model, the current fundamentals of the economy are unobserved, such that financial-market participants (traders from now on) have to rely on public indicators to form their expectations. The link of these indicators to the fundamentals is time-varying, e.g., because of developments that are unrelated to fundamentals but still have a bearing on a particular indicator release.[14] Traders receive private signals about the link of the indicators to the fundamentals, or,

[13] We note, however, that simply controlling for the change in the term structure of interest—measured here by the change in the yield of the US 10-Year T-Note Future minus the change in the yield of the US 2-Year T-Note Future—in the 10-minute window around our event has hardly any effect (results available upon request). We leave a deeper analysis of monetary policy uncertainty and its effect on the stock market reaction to news, e.g., via changes in the whole yield curve, for future research.

[14] An example of such a weak link is the improvement of official labor market statistics running up to 2014, which was partly driven by discouraged workers leaving the labor force, and not only by an improving

Figure 4: Intra-period model timing



equivalently, have a private and idiosyncratic interpretation of current circumstances. These private signals are dispersed in times of weak links between indicators and fundamentals, muting the market reaction to the subsequent indicator release. Uncertainty about current fundamentals, on the other hand, results from a higher volatility of shocks that move fundamentals. Information becomes more valuable in times of high uncertainty, such that markets react stronger to indicator releases for a given perceived link between these indicators and fundamentals.

Figure 4 visualizes the intra-period timing of the model. In step 1 of each period, expectations of traders are formed on the basis of last period's information. These expectations are surveyed and published by a media firm in step 2 of each period. Traders adjust their expectations in response to the publication. Finally, the indicator is released in step 3. The relation to our empirical setup is thereby as follows. Steps 1 and 2 happen before the indicator release in step 3, such that traders know about the distribution of forecasts before the release. Since Bloomberg forecasts are available before the empirical indicator release, this timing corresponds as closely as possible to actual events. The pre-release window employed in our regressions corresponds to the situation after the survey release in step 2; no new information arrives between the survey and the indicator releases. At the time of the indicator release, prices change accordingly. In the model this takes place in step 3, in our empirical setup in the post-release window. We therefore compare the predictions of price

economic situation (Yellen, 2014). This was accompanied by an unusually large forecast dispersion for initial jobless claims in early 2014.

changes before and after step 3, derived in Section 5.2, with the observed changes between the empirical pre- and post-release windows.

5.1 Setup

There is a fundamental factor, think of technology, that represents the potential of the economy and determines long-run profits of firms and, hence, current stock prices. Aggregate (log-) technology x_t follows a random walk,

$$x_t = x_{t-1} + \varepsilon_t \ , \tag{3}$$

with $\varepsilon_t \sim N(0, \sigma_\varepsilon^2)$. Agents do not observe technology directly. At various points in time, however, indicators that are linked to technology are released, from which agents can infer about current technology. Depending on the current combination of shocks in the economy, measurement error, and short-term developments, indicators may be more or less tightly linked to the underlying potential. They are, hence, only noisy signals about technology,

$$i_t = \varepsilon_t + \nu_t(i) \ , \tag{4}$$

where the noisy component $\nu_t(i)$ is a draw from the distribution $N(\mu_{\nu,t}, \sigma_{\nu,t}^2)$, which exhibits time-varying mean and variance. The mean and variance are uncorrelated over time. Note that σ_ε^2 is constant, which simplifies the notation and the model solution without changing the qualitative results. What ultimately matters is the relative size of these two variances, such that σ_ε^2 can be normalized to a constant. This setup captures, in a stylized manner, the notion that indicators are influenced by other factors besides the fundamentals of interest and that the disagreement among financial-market participants about the current importance of such factors may vary over time.

There is a unit mass of traders in the economy, who trade stocks based on private and public information. All information from period $t-1$ is released at the beginning of the current period. Hence, x_{t-1} summarizes all relevant information about technology at this point and is publicly known. Additionally, at the same time each trader $j \in \{0, 1\}$ observes a private signal, $s_t(j)$, about the link between technology and a specific indicator. This signal is another draw from the distribution $N(\mu_{\nu,t}, \sigma^2_{\nu,t})$ of the noisy component.

5.2 Changes in expectations and stock prices

Given her private signal, trader j forms an individual estimate of $\mu_{\nu,t}$. Because of her limited information, $E^j_{t,1}\mu_{\nu,t} = s_t(j)$ and, hence, she predicts i_t as $E^j_{t,1} i_t = s_t(j)$. That is, expectations will be more dispersed if $\sigma^2_{\nu,t}$ is high and $s_t(j)$ is consequently more dispersed. Here, $E^j_{t,1}$ represents the estimates of trader j in the first stage of period t.

Since the expectations of a unit mass of traders are published in step 2 of each period, traders learn the exact values of $\mu_{\nu,t}$ and $\sigma^2_{\nu,t}$ from the survey publication and all forecasters now have homogeneous expectations. In particular, they estimate

$$\begin{aligned} E_{t,2}\mu_{\nu,t} &= \int_0^1 s_t(j)dj = \mu_{\nu,t} \\ E_{t,2}\sigma^2_{\nu,t} &= \int_0^1 \left(s_t(j) - \mu_{\nu,t}\right)^2 dj = \sigma^2_{\nu,t} \ . \end{aligned} \tag{5}$$

At this point, expectations regarding the indicator are therefore $E_{t,2} i_t = \mu_{\nu,t}$. Forecasters cannot, however, infer anything about technology in addition to x_{t-1}, which is public knowledge. Hence, no price change takes place after the release of the survey.

After the indicator is released in the third stage, new expectations regarding x_t are formed. This formation follows a standard signal-extraction problem, where expectations are given by

$$E_{t,3}x_t = x_{t-1} + \rho_{i,t}(i_t - \mu_{\nu,t}) \quad \text{with} \quad \rho_{i,t} = \frac{\sigma^2_\varepsilon}{\sigma^2_\varepsilon + \sigma^2_{\nu,t}} \ . \tag{6}$$

Traders then trade proportionally to $E_{t,3}x_t - E_{t,2}x_t = E_{t,3}x_t - x_{t-1} = \rho_{i,t}(i_t - \mu_{\nu,t})$. That is, only if the indicator comes in as expected on average, stock prices do not change.

The resulting price changes correspond to our empirical observations, such that the model predictions are in line with our findings. In times of high expectation dispersion (high $\sigma^2_{\nu,t}$), traders react less to new information than in times of low expectation dispersion. At the same time, in times of higher uncertainty (high σ^2_{ε}), the reaction to news is stronger.

6 Conclusion

One of the most important questions in asset pricing is how market prices react to news. We have shown both theoretically as well as empirically that the link between macroeconomic news and stock markets is affected by both uncertainty and expectation dispersion, but in opposite directions. We rationalize this finding by linking expectation dispersion to the (perceived) information content of news, and uncertainty to the economic value of this information. As both variables are changing over time, also the implied strength of the market reaction to news is time varying.

This insight has more general implications. For example, it speaks against tying policy reactions, such as monetary policy actions, to the development of certain indicators, like those pertaining to labor-market developments. Instead, the implication of macroeconomic news for the estimate of the current economic fundamentals has to be evaluated in the light of additional information. One important variable in this regard is expectation dispersion. Furthermore, our results underline that, depending on the context, expectation dispersion and uncertainty can be very different objects, although they are often used interchangeably.

References

Andersen, Torben G., Tim Bollerslev, Francis X. Diebold, and Clara Vega (2007). "Real-time price discovery in global stock, bond and foreign exchange markets". *Journal of International Economics 73* (2), 251–277.

Baker, Scott R., Nicholas Bloom, and Steven J. Davis (2016). "Measuring economic policy uncertainty". *Quarterly Journal of Economics 131* (4), 1593–1636.

Beechey, Meredith J. and Jonathan H. Wright (2009). "The high-frequency impact of news on long-term yields and forward rates: is it real?" *Journal of Monetary Economics 56* (4), 535–544.

Boyd, John H., Jian Hu, and Ravi Jagannathan (2005). "The stock market's reaction to unemployment news: why bad news is usually good for stocks". *Journal of Finance 60* (2), 649–672.

Ehrmann, Michael and David Sondermann (2012). "The news content of macroeconomic announcements: what if central bank communication becomes stale?" *International Journal of Central Banking 8* (3), 1–53.

Fleming, Michael J. and Eli M. Remolona (1999). "Price formation and liquidity in the U.S. treasury market: the response to public information". *Journal of Finance 54* (5), 1901–1915.

Gilbert, Thomas (2011). "Information aggregation around macroeconomic announcements: revisions matter". *Journal of Financial Economics 101* (1), 114–131.

Gilbert, Thomas, Chiara Scotti, Georg Strasser, and Clara Vega (2017). "Is the intrinsic value of a macroeconomic news announcement related to its asset price impact?" *Journal of Monetary Economics 92*, 78–95.

Giordani, Paolo and Paul Söderlind (2003). "Inflation forecast uncertainty". *European Economic Review 47* (6), 1037–1059.

Husted, Lucas, John Rogers, and Bo Sun (2020). "Monetary policy uncertainty". *Journal of Monetary Economics 115*, 20–36.

Jurado, Kyle, Sydney C. Ludvigson, and Serena Ng (2015). "Measuring uncertainty". *American Economic Review 105* (3), 1177–1216.

Kurov, Alexander and Raluca Stan (2018). "Monetary policy uncertainty and the market reaction to macroeconomic news". *Journal of Banking & Finance 86*, 127–142.

Lahiri, Kajal and Xuguang Sheng (2010). "Measuring forecast uncertainty by disagreement: the missing link". *Journal of Applied Econometrics 25* (4), 514–538.

Law, Tzuo-Hann, Dongho Song, and Amir Yaron (2020). "Fearing the Fed: how Wall Street reads Main Street". Mimeo. Wharton School.

Ludvigson, Sydney C., Sai Ma, and Serena Ng (2021). "Uncertainty and business cycles: exogenous impulse or endogenous response?" *American Economic Journal: Macroeconomics 13* (4), 369–410.

McQueen, Grant and V. Vance Roley (1993). "Stock prices, news, and business conditions". *Review of Financial Studies 6* (3), 683–707.

Scotti, Chiara (2016). "Surprise and uncertainty indexes: real-time aggregation of real-activity macro-surprises". *Journal of Monetary Economics 82*, 1–19.

Yellen, Janet L. (2014). "Labor market dynamics and monetary policy". Speech at the Federal Reserve Bank of Kansas City Economic Symposium, Jackson Hole, Wyoming.

Zarnowitz, Victor and Louis A. Lambros (1987). "Consensus and uncertainty in economic prediction". *Journal of Political Economy 95* (3), 591–621.

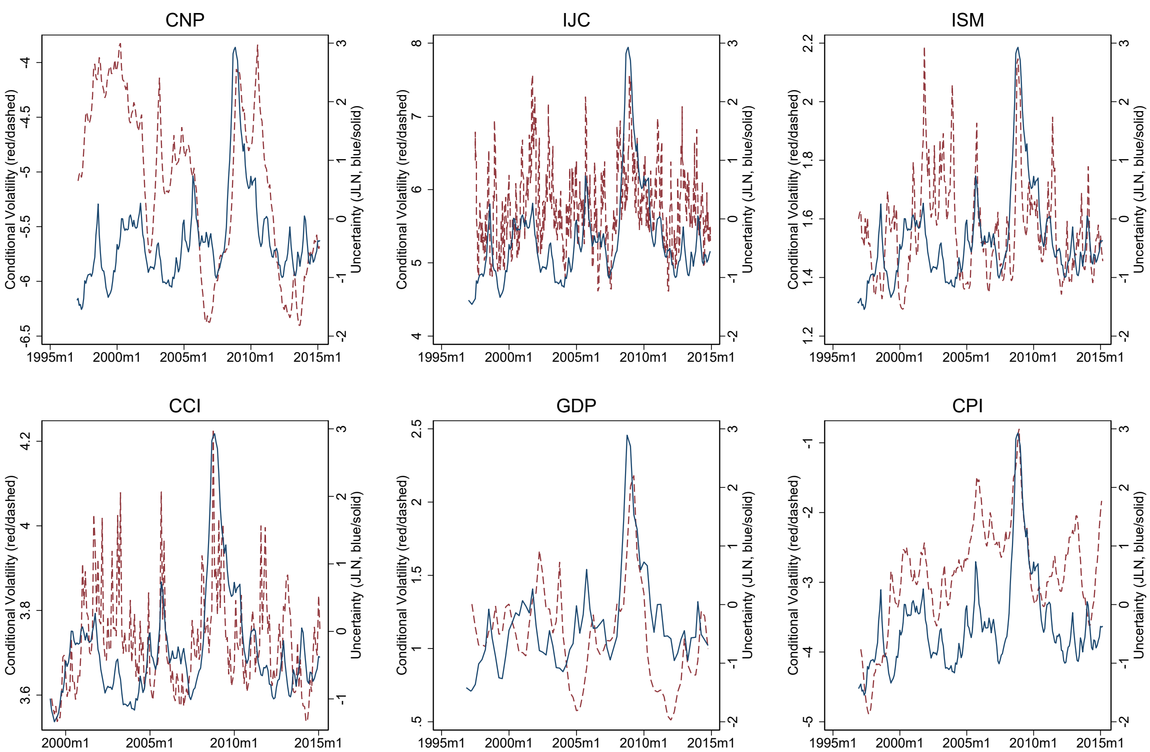
A Appendix

Table A.1: Information on forecast data

Indicator	Acronym	Freq.	First obs.	# obs	Avg. # forecasters
Chg. in non-farm payrolls	CNP	m	01/08/1997	197	70.5
Initial jobless claims	IJC	w	11/02/1999	824	36.9
ISM manufacturing index	ISM	m	01/06/1998	195	64.6
Conf. Board cons. confidence	CCI	m	23/02/1999	193	59.4
GDP growth	GDP	q	30/04/1998	66	68.3
CPI inflation	CPI	m	16/06/1998	196	66.5

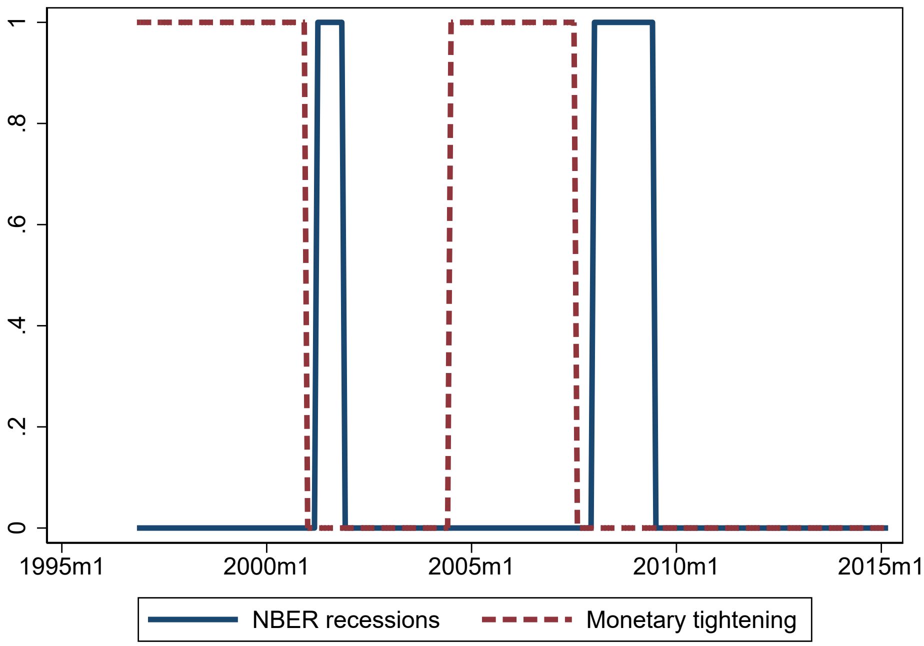
Notes: Observed frequencies in our sample are weekly (w), monthly (m), and quarterly (q). The last observations in our sample are from March 2015.

Figure A.1: Aggregate uncertainty measure vs. index-specific uncertainty



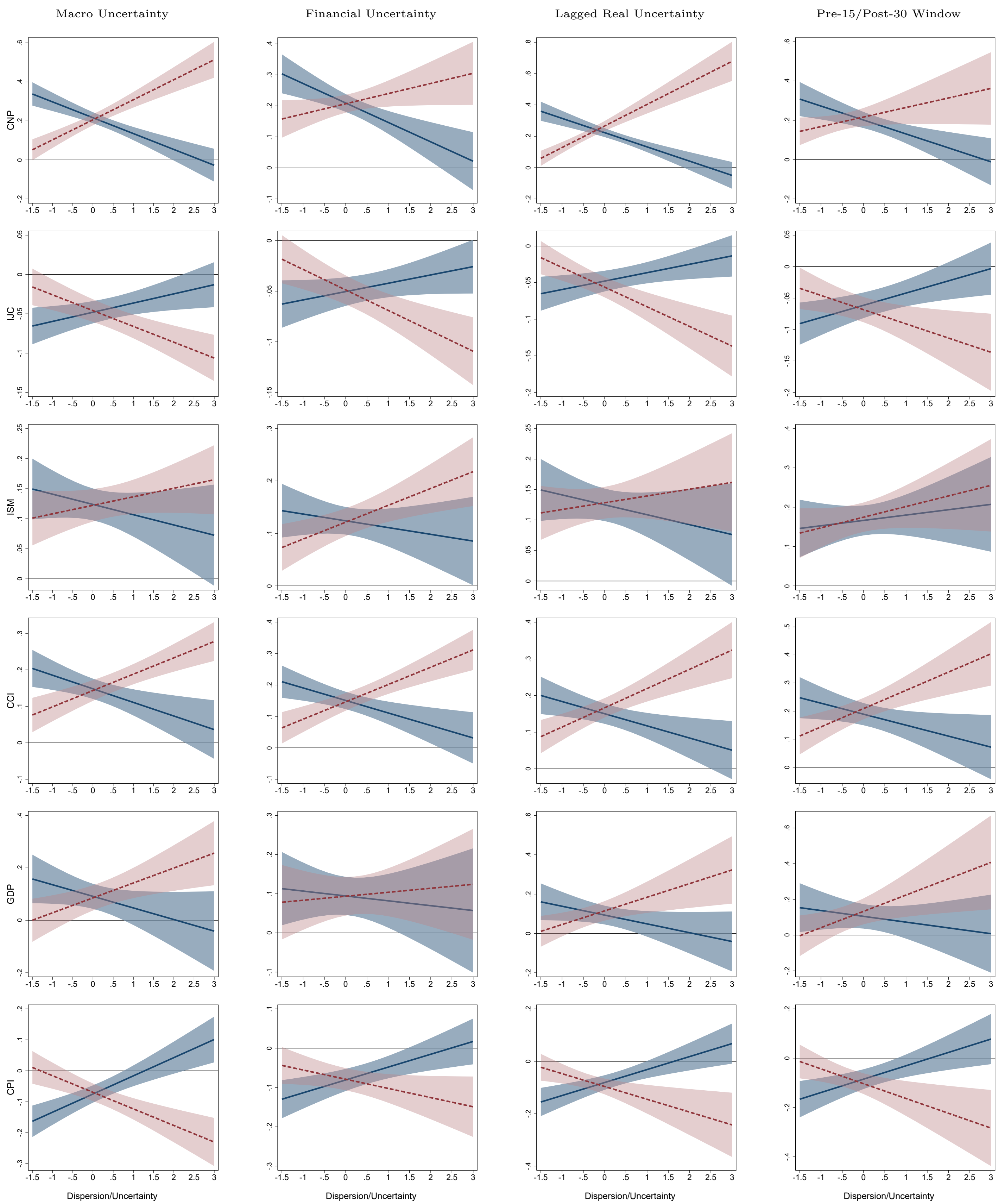
Notes: Ludvigson et al. (2021) (real) aggregate uncertainty measure (blue solid) against index-specific uncertainty based on univariate SV models (red dashed).

Figure A.2: Recession/non-recession and monetary tightening/loosening regimes



Notes: Recessions based on NBER business cycle dating. Start of a monetary tightening period defined by the date of the first increase of the Federal Reserve target rate in one cycle and the end by the date just before the first interest rate reduction.

Figure A.3: Additional robustness checks: uncertainty measures and window size



Notes: see Figure 2.