Narrative Monetary Policy Uncertainty

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Abstract

We develop a novel method to capture monetary policy uncertainty reflected in the media. The proposed uncertainty measure is constructed using advanced natural language processing techniques and can be computed daily, even when news coverage is low. We find an average increase in uncertainty on days leading to scheduled central bank announcements and a significant decrease on days after announcements. However, following negative news on announcement dates, uncertainty increases. At lower frequency, we show that the uncertainty measure responds to changes in macroeconomic fundamentals such as unemployment, housing prices, and inflation.

Keywords: monetary policy uncertainty, risk premia, central bank communication, machine learning, natural language processing

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1 Introduction

Monetary policy announcements are instrumental in shaping the expectations of economic agents and maintaining the stability of the financial system. Policy changes' influence on equity prices and long-term real interest rates is well-studied and empirically validated.[1] A more recent thread of studies goes beyond policy changes and focuses on the role of policy uncertainty and how it is transmitted to financial markets. However, identifying this effect remains challenging considering that there is no one-size-fits-all method to quantify monetary policy uncertainty.

One approach to measuring uncertainty is by eliciting its impact on financial markets. Bauer et al. [2021] do so by looking into the prices of Eurodollar options and futures in the cycle between FOMC announcements. The uncertainty measure proposed is related to the implied conditional volatility of future LIBOR, which is considered a benchmark short-term interest rate. An alternative approach involves analyzing the narrative around monetary policy found in newspapers and the general media. The assumption is that if the readership cares about policy changes and forward guidance, and if uncertainty about those is significant, then the level of uncertainty will be reflected in the tone used by the media to describe the state of the economy. Along these lines, several text-based policy uncertainty measures have recently been introduced. The seminal work of Baker et al. [2016] gave rise to the widely-used Economic Policy Uncertainty (EPU) and Monetary Policy Uncertainty (MPU) indices, while Husted et al. [2020] constructed an alternative monetary policy uncertainty index (referred to as Husted-Rogers-Sun MPU, or HRS-MPU) based on the same methodology. These measures mostly rely on the occurrence of particular keywords in articles. The methodology lacks the fine granularity required to capture nuance in language; it can only identify the presence of uncertainty in an article but not its level. Being keyword-based also means that a large supply of articles is necessary in order to aggregate data meaningfully. This limits the frequency with which uncertainty can be measured with confidence. Moreover, it is not yet established in the literature whether text-based and market-based policy uncertainties are directionally aligned, especially considering that several macroeconomic variables may influence market-based proxies of uncertainty.

In this paper, we propose a novel soft information measure that quantifies the level of language uncertainty for any topic, ranging from news about monetary policy to news about

[1] See, for example, Kuttner [2001], Bernanke and Kuttner [2005], Swanson [2021], Savor and Wilson [2013], Lucca and Moench [2015], Nakamura and Steinsson [2018], Cieslak et al. [2019], Boguth et al. [2019], among others.

the housing market and the energy sector.[2] We apply a state-of-the-art language model[3] to the textual content of news articles and obtain article-level uncertainty scores that can be aggregated within various time periods. The model takes language context into account, making it possible to obtain trustworthy scores even from a handful of articles (our methodology does not require but can benefit from a large article count). By forming a measure of the level, rather than only the presence, of uncertainty in a given news article, more informative results can be obtained with fewer articles. This is important when analyzing uncertainty toward topics with low coverage and becomes essential in event studies concerned with how financial markets and macroeconomic fundamentals respond to monetary policy announcements.[4]

Our method, like the EPU and MPU, relies on narratives and text analysis to address a wide range of uncertainties in the economy, not just limited to market-based monetary policy uncertainty (such as using Eurodollar option volatility as a proxy). This becomes particularly relevant as many central banks in developed countries have resorted to two alternative measures after exhausting conventional interest rate cuts. These measures involve implementing large-scale quantitative easing and providing explicit forward guidance, both of which have been frequently discussed in the news since the global financial crisis of 2008/2009.

We focus on monetary policy and show that the proposed uncertainty measure, which we refer to as Narrative Monetary Policy Uncertainty (NMPU), positively correlates with the EPU and MPU indices at daily and monthly frequencies. Considering the US and Canadian economies separately, we find that FOMC meetings and Bank of Canada interest rate announcements lower media uncertainty on average, while uncertainty builds up in the days preceding the announcements. In general, equity returns are negatively correlated with the level of uncertainty after announcements and with the change in uncertainty between the days leading to the announcement and the days following. However, bad news around monetary policy, which is proxied by negative equity returns on the announcement day, correlate with an increase in uncertainty. In Canada, we expose a difference between newswires in terms of how uncertainty around monetary policy is reported. Finally, we show that the proposed uncertainty measure responds to macroeconomic fundamentals in the US, such as the unemployment rate, Consumer Price Index, the housing index (Case-Shiller), and the federal funds effective rate. However, the sensitivity depends on the source used to measure uncertainty since periodicals in the US focus on macroeconomic issues in varying degrees.

[2]Keyword search can be used to obtain articles from a specific database, but the proposed uncertainty measure does not rely on the keywords used and is universally applicable to any topic.

[3]The model is based on the transformer architecture proposed by Devlin et al. [2019a]

[4]Applications of contextual uncertainty include corporate-level measurements and analysis of uncertainty in countries with lower coverage (*e.g.*, Canada).

2 NMPU based on Language Models

In our methodology we interpret language uncertainty as any instance in which writers intentionally convey the fact that they do not have all the information on a matter, because the situation is inherently unpredictable, or because they're speculating about hypothetical future scenarios. Uncertainty can be expressed in many ways, including questions, tentative statements, expressions of doubt, or with the use of "hedging" words. It is evident that to quantify the level of uncertainty in an article it does not suffice to simply identify whether the word "uncertain" or derivatives and synonyms thereof are present. This typical approach ignores the space of possibilities when it comes to expressing uncertainty. The problem calls for symbolic or data-driven solutions. We focus on the latter and particularly on natural language processing (NLP) techniques that have now reached maturity when it comes to semantic analysis and language understanding.

The field of NLP recently experienced a major breakthrough stemming from a new class of language models referred to as *transformers*, and specifically an architecture called Bidirectional Encoder Representations from Transformers (BERT). To this day transformer models are considered the state-of-the-art NLP technique, having superseded all other language models.[5] BERT models involve a process, referred to as pre-training, where deep neural networks are trained using unlabeled text in order to predict missing words in sentences based on the "right" and "left" context of each missing word (Devlin et al. [2019b]). The premise is that pre-trained models must learn the basic structure, rules and organization of language to be able to fulfill the prediction task accurately. Pre-trained models can then be fine-tuned (*e.g.*, by supervised learning) with only minor modifications to produce cutting-edge models for various downstream tasks. The ability to take a publicly available pre-trained BERT model and fine-tune it for a downstream task such as uncertainty analysis is broadly known as *transfer learning*. Fine-tuning only requires a small set of examples (*e.g.,* examples of words/sentences that express uncertainty) in order to achieve robust performance, because the fine-tuned model does not need to re-learn language properties

2.1 Data

In the ProQuest Database we search for articles related to monetary policy in major newspapers for both the US and Canada. The keywords used to identify relavent articles are listed in Table A1. For the US, we search for news articles in "The Wall Street Journal" (WSJ) and "New York Times" (NYT) data sources. We sample from newspapers only and exclude other source types such as magazines under the same publication. The sample period begins

[5] Indicatively, GPT models, such as OpenAI's ChatGPT are also based on the transformer paradigm.

on Jan 2, 1984 and ends on Mar 22, 2023 for both publications. This gives a total of 70,356 articles from WSJ and 21,101 articles from NYT. For Canada, we search for news articles in the National Post. The sample period begins on Oct 27, 1998 and ends on Mar 22, 2023. This gives a total of 10,758 articles. We remove all special characters, numbers and multi-spaces from each news article, lemmatize all the words and split the article into sentences to reduce the dimensionality of the problem.

2.2 NMPU Index Construction

We apply a publicly available BERT model[6] on each article, which is fine-tuned to the task of word-level uncertainty detection. The model returns a list of all words that express uncertainty in each article and we compute the article's uncertainty score as the number of words expressing uncertainty over the total number of words in the article. An alternative approach is to use a fixed dictionary of uncertainty words commonly used in finance and perform the same calculations as described above. One such dictionary is the popular lexicon proposed by Loughran and McDonald [2011]. Apart from our method we also apply this dictionary-based technique and treat it as context-agnostic baseline. We anticipate that the BERT-based method will prove to be superior for two main reasons: (a) dictionary-based methods are *static*, that is, words that imply uncertainty are always the same across various time periods and periodicals and, (b), they ignore context, where in reality context gives rise to the meaning of a word and the implications of using it.[7]

2.3 Daily and Monthly NMPU

With the raw uncertainty score assigned to each available monetary policy article from a single publication, we take a daily average to get a raw uncertainty score for day t, denoted UNC_t. If there are no articles on day t, UNC_t is assumed to be 0 in the following calculation. We keep only the trading day scores, and subtract the 252-day trailing average to obtain the

[6]The model is available at https://huggingface.co/jeniakim/hedgehog

[7]Consider for example a phrase taken from a WSJ article on March 16, 2023: "Last week's jobs report told a similar story: The US economy added 311,000 jobs in February, more than economists expected but down sharply from January's 517,000." A dictionary-based method will tag the word "expected" since it is considered an uncertainty-related word in the Loughran and McDonald [2011] dictionary. A language model, such as BERT, takes the entire sentence into account, recognizes that "expected" refers to uncertainty in the past, and does not classify it as a word that implies uncertainty about current or future outcomes. The word will, correctly, not contribute to the uncertainty score of that article. Similarly, cases of negation, co-reference and ambiguity, all of which may affect uncertainty levels are correctly resolved by BERT models.

NMPU on day t, denoted NMPU_t:

$$\text{NMPU}_t = \text{UNC}_t - \frac{1}{252} \sum_{k=t-251}^{t} \text{UNC}_k. \tag{1}$$

This calculation is done on news from Wall Street Journal and on news from New York Times to get the publication specific scores, $\text{NMPU}_t^{\text{WSJ}}$ for Wall Street Journal and $\text{NMPU}_t^{\text{NYT}}$ for New York Times. To get the combined score on day t, we calculate the average of $\text{NMPU}_t^{\text{WSJ}}$ and $\text{NMPU}_t^{\text{NYT}}$. If one of the publications is not available on day t, then the combined score will be the NMPU_t of the other publication. For the publication specific monthly scores $\text{NMPU}_t^{\text{WSJ}}$ and $\text{NMPU}_t^{\text{NYT}}$ of month t, we start with the raw daily scores UNC_t, keep only the trading day values, then average over the month. Then NMPU_t of a month t is defined to be the average of $\text{NMPU}_t^{\text{WSJ}}$ and $\text{NMPU}_t^{\text{NYT}}$. For Canadian data, we keep daily $\text{NMPU}_t = \text{UNC}_t$ whenever UNC_t is available and calculate monthly NMPU_t by a simple average over the month, as the news count and coverage is much lower and setting 0s to days without news will make 0 the dominant value in the timeseries.

2.4 NMPU Properties

We first demonstrate how NMPU correlates with existing narrative-based and market-based uncertainty measures. The main narrative-based measure we consider is the EPU by Baker et al. [2016].[8] Moreover, we consider indices such as the CBOE Volatility Index (VIX), the Merrill Lynch Option Volatility Estimate (MOVE) and the LIBOR-based uncertainty measure by Bauer et al. [2021] (denoted MPU-MKT). Figure 1 illustrates the monthly NMPU paired with the above narrative-based and market-based indices. Table 1 shows correlations at the daily and monthly frequency between NMPU and the aforementioned measures that are available at both frequencies, focusing on the US economy. Since MPU and HRS MPU are not available at daily frequency, we include them in Table A2 found in the Appendix.

At the daily frequency, we find that NMPU obtained from New York Times positively correlates with marked-based measures and even more so with narrative-based measures. NMPU based on Wall Street Journal is directionally aligned with narrative-based measures. Interestingly, its correlation to market-based measures is negative. Similar conclusions are drawn at the monthly frequency. The LIBOR-based MPU-MKT by Bauer et al. [2021] positively correlates with VIX and MOVE. At the monthly frequency NMPU obtained from WSJ is inversely correlated to MPU-MKT. Finally, it is worth noting that EPU, MPU,

[8]Results for MPU by Baker et al. [2016] and HRS-MPU by Husted et al. [2020] can be found in the Appendix, Figure A1.

HRS-MPU move with VIX but have a weaker and often negative statistical relationship to the MOVE index. The above results are an indication that different uncertainty measures may have varying interpretations and applicability; some may serve as proxies for market volatility, while others are better at capturing uncertainty about interest rates. With our methodology which allows us to obtain reliable scores even from a single news source, we find that uncertainty reported in different periodicals may also correspond to these alternative interpretations. When it comes to Canadian newspapers, we find that NMPU is positively correlated with EPU (the correlation is 0.324). The latter is the only other uncertainty index we can reliably obtain for Canada.

3 NMPU and Policy Announcements

In this section we focus our attention to the behavior of NMPU around monetary policy announcements. We consider FOMC meetings starting on Feb 04, 1994, and fixed announcement date (FAD) press releases by the Bank of Canada starting on Aug 28, 2001.

To perform the event study, for each announcement day τ we define $\text{NMPU}_{\tau,[a,b]}$ to be the mean NMPU in the window $[\tau + a, \tau + b]$ $(a < b)$. Specifically:

$$\text{NMPU}_{\tau,[a,b]} = \frac{1}{|T|} \sum_{t \in T} \text{NMPU}_t, \text{ where } T = \{t \in [\tau + a, \ldots, \tau + b] : \text{NMPU}_t \text{ is defined}\}. \quad (2)$$

We also define $\Delta\text{NMPU}_{\tau,[a,b]}$ $(a < 0,\ b > 0)$ to be the change of average NMPU before and after announcement. Specifically:

$$\Delta\text{NMPU}_{\tau,[a,b]} = \text{NMPU}_{\tau,[1,b]} - \text{NMPU}_{\tau,[a,-1]}. \quad (3)$$

Figure 2 shows that the average NMPU starts building up in the 5 days prior to the FOMC meeting and peaks on the day following the meeting when newspapers discuss the event with complete information. Uncertainty drops sharply immediately after and is gradually resolved within the first 5 post-announcement days, on average. Both in the US and Canada, we observe weekly seasonality in uncertainty before and after announcements. Finally, in the US, when uncertainty is sourced from different newspapers (WSJ and NYT) its peaks appear shifted by a day. NMPU^{WSJ} peaks on the day before the FOMC meeting, while NMPU^{NYT} peaks on the day after the FOMC meeting. Similar conclusions are drawn when examining NMPU's movements around BoC FAD press releases, as shown in Figure A3 in the Appendix.[9]

Next, we study how NMPU and changes in NMPU respond to announcement-day returns. Specifically, we regress $\text{NMPU}_{\tau,[1,3]}$ and $\Delta\text{NMPU}_{\tau,[-3,3]}$ on the returns of the S&P500 index observed on the day of the FOMC meeting (day τ). We control for absolute announcement-day returns. Orthogonally, to examine the effects of bad (*e.g.,* "hawkish") monetary policy news we regress $\text{NMPU}_{\tau,[1,3]}$ and $\Delta\text{NMPU}_{\tau,[-3,3]}$ on the dummy indicator variable $\mathbb{1}_{\text{Ret}_\tau<0}$. In Panel A of Table 2 we report results. We also replicate the regression models but with EPU, MPU-MKT and VIX as the response variables, and we report results in Panel B. We find a statistically significant relationship where positive market returns on announcement days are associated with reduced NMPU (negative β coefficient) over the following 3 days. This behavior is also seen when it comes to the market-based index, MPU-MKT. Instead, the daily EPU index by Baker et al. [2016] yields a positive β coefficient. In scenarios where news are "bad", we observe that poor (negative) returns on FOMC meeting days are associated with an increase in uncertainty sourced from WSJ over the following 3 days after the announcement. This increase is consistent over time but results are mixed when applied to a less business focused paper such as NYT. MPU-MKT and VIX react similarly to bad news, but EPU responds in the opposite manner.

Going beyond the short-window increase (decrease) in NMPU following negative (positive) announcement-day returns, we are also interested in how uncertainty evolves over longer time windows following FOMC announcements. To this end, we calculate the average cumulative NMPU for the 30 days following FOMC announcements. To illustrate how the polarity of announcement-day news affects uncertainty over longer horizons, we calculate cumulative NMPU conditional on announcement-day returns (positive vs. negative). Figure 3 illustrates that narrative uncertainty captured by WSJ continues growing following "hawkish" news for the entire window, whereas uncertainty drops and is continuously resolved over time in the case of good news. When it comes to NYT, uncertainty remains elevated when FOMC news are bad, and abruptly drops and remains supressed in the opposite scenario. In both cases, an uptick in uncertainty is observed towards the end of the 30-day window, which coincides with the days leading up to the next FOMC meeting; uncertainty starts building up. The same figure also shows that the gap between uncertainty levels in the "hawkish" and "dovish" scenarios continues growing over the 30-day period.

To showcase that the advanced NLP method is superior to a context-agnostic method, we repeat a similar experiment but use words from the dictionary of Loughran and McDonald [2011] to calculate article-level uncertainty. We refer to the measure as NMPU-LM and we

[9]We find that the build-up and resolution window is narrower. Uncertainty rises sharply within 2 days prior to the event. Then, the press release rapidly lowers uncertainty within the span of 2 days.

regress NMPU-LM and changes in NMPU-LM on FOMC announcement returns without controlling for absolute returns this time. Table A3 in the Appendix includes results. For reference we also include results of the same regression for the NLP-based NMPU (referred to as NMPU-ML in that context) and other existing measures (EPU, MPU-MKT and VIX). Despite the fact that the coefficient sign is the one expected (negative) we find that the response of NMPU-LM is not statistically significant. Finally, we repeat the same analysis focusing on how NMPU derived from Canadian newspapers responds to BoC FAD press releases. Conclusions are similar to those drawn from the US study. Regression results are summarized in Table A5 in the Appendix.

4 NMPU and Macroeconomic Fundamentals

Studies by Bansal and Shaliastovich [2011], Kacperczyk et al. [2016] have established a link between endogenous attention and uncertainty. Specifically, it is shown that voluntary investor attention rises with economic uncertainty and risk aversion. Subsequent studies by Ai and Bansal [2018], Fisher et al. [2022] expose a relationship between attention, macroeconomic fundamentals and announcement risk premia. This thread of work motivates us to empirically study how low-frequency NMPU responds to macroeconomic fundamentals, and to understand whether macroeconomic drivers of NMPU are different from those driving market-based measures of uncertainty. To this end we consider fundamentals such as unemployment, the housing index (Case-Shiller U.S. National Home Price Index), Consumer Price Index, Fed Fund rates and the 10-year T-bill yield.

Let F_t^M denote a fundamental available at a calendar month frequency, where t indexes months. Let F_t^Q, F_t^Y, and F_t^{4Y} be the moving averages over windows of size 3, 12, and 48 months, ending at t (*i.e.*, $F_t^Q = \frac{1}{3}\sum_{k=0}^{2} F_{t-k}^M$). We then define a decomposition of F_t^M as follows:

$$\begin{aligned} F_t^M &= \left(F_t^M - F_t^Q\right) + \left(F_t^Q - F_t^Y\right) + \left(F_t^Y - F_t^{4Y}\right) + F_t^{4Y} \\ &= F_t^{M-Q} + F_t^{Q-Y} + F_t^{Y-4Y} + F_t^{4Y} \end{aligned} \tag{4}$$

where each term is a detrended moving average over the appropriate calendar interval (month, quarter, year, four years). Similar types of expansions are used to capture variability in persistence of the fundamentals and long-cycle dependencies by Fisher et al. [2022], Ortu et al. [2013], Calvet and Fisher [2007].

We regress NMPU on the detrended moving averages of fundamentals and the absolute values of the detrended moving averages:

$$\text{NMPU}_t = \alpha + \beta_1 F_t^{M-Q} + \beta_2 F_t^{Q-Y} + \beta_3 F_t^{Y-4Y} + \beta_4 |F_t^{M-Q}| + \beta_5 |F_t^{Q-Y}| + \beta_6 |F_t^{Y-4Y}| + \epsilon_t, \tag{5}$$

We expect that large changes in macroeconomic variables irrespective of direction should lead to increased levels of monetary uncertainty. This is captured by the coefficients of the absolute value terms in Eq. 5. On the other hand, asymmetries in how uncertainty responds (*i.e.,* bigger changes for "bad" changes in fundamentals) are expected to be shown by the coefficients of the remaining terms.

Results for the NMPU measure are in Panel A of Table 3. The adjusted R^2 reaches up to 19.1% across all regressions, and all of them have at least one statistically significant coefficient, with the Federal fund rate being an exception. We find that large changes in the absolute values for housing index, CPI, unemployment rates and 10 year treasury bond yield leads to more uncertainty about the monetary policy as measured by NMPU. However, we find that shocks in CPI at the yearly frequency are associated with a drop in uncertainty. Panel B in the same table shows results when we regress MPU-MKT on the same macro variables. The regressions expose significance in the effect of macro variable changes. However, the direction (sign of coefficients) does not always agree with what is observed in NMPU regressions. For instance, a large change in unemployment leads to a drop in MPU-MKT, but NMPU rises. On the other hand, MPU-MKT has a stronger response to Fed fund rate changes, which is expected since LIBOR closely tracks the key interest rates by the Federal Reserve.

5 Conclusion

We showed how advanced language models can be used to measure uncertainty about monetary policy in news articles. Using a sample of about 70 thousand news articles from 1984 to 2023, we construct a monetary policy uncertainty index for the US. The index can be reliably computed daily since the proposed method can generate meaningful uncertainty levels even with a few articles available. We show that the new uncertainty measure: (a) positively correlates with existing narrative-based measures that are typically restricted to monthly frequencies, (b) on average it builds up before FOMC announcements and is lowered in the days following, (c) has a statistically significant response to "hawkish" announcements, appearing elevated after bad news, and (d) responds to large changes in macroeconomic fundamentals such as CPI, unemployment and housing prices. We repeat the empirical study around Bank of Canada FAD press releases and observe a similar behavior when uncertainty is measured using Canadian news sources.

The primary focus of this paper is on monetary policy, but the measure can be applied to any topic, including sectors such as housing, energy, and other macroeconomic fundamentals such as inflation. We plan to extend the study and empirically evaluate the measure's ability to forecast changes in macro variables, and sector-level returns and volatility. Finally, we plan to build upon existing frameworks that link endogenous attention -which is partly driven by uncertainty- to announcement risk premia and evaluate whether the proposed uncertainty measure can serve as an instrument for future risk premia following central bank announcements.

Figure 1: US NMPU, compared with exisiting uncertainty measures

This figure shows the monthly US NMPU with EPU, Market-based MPU (MPU-MKT), VIX and MOVE from Jan, 1984. All the scores are smoothed by a 12 month moving average. The gray vertical bars are NBER recessions.

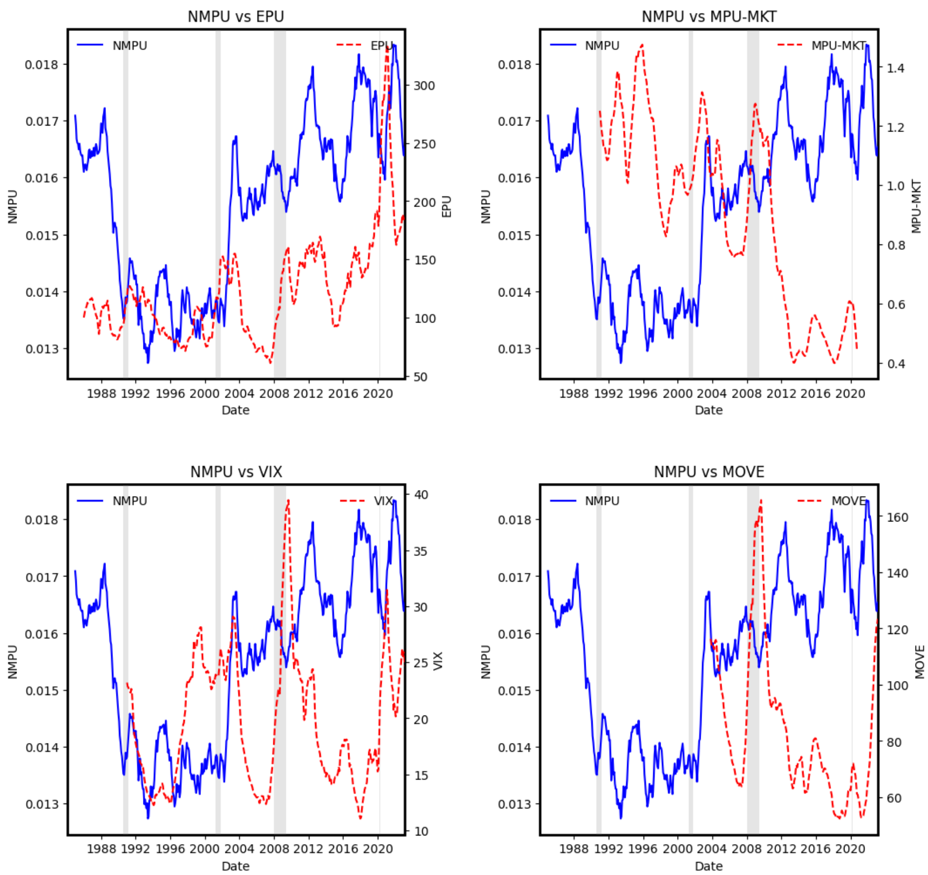

Figure 2: US NMPU around FOMC meetings

This figure shows the average US NMPU from WSJ ($NMPU^{WSJ}$), NYT ($NMPU^{NYT}$) and combined (NMPU), using both Loughran McDonald (LM) and Machine Learning (ML) scores, around FOMC meetings, starting at Feb 04, 1994.

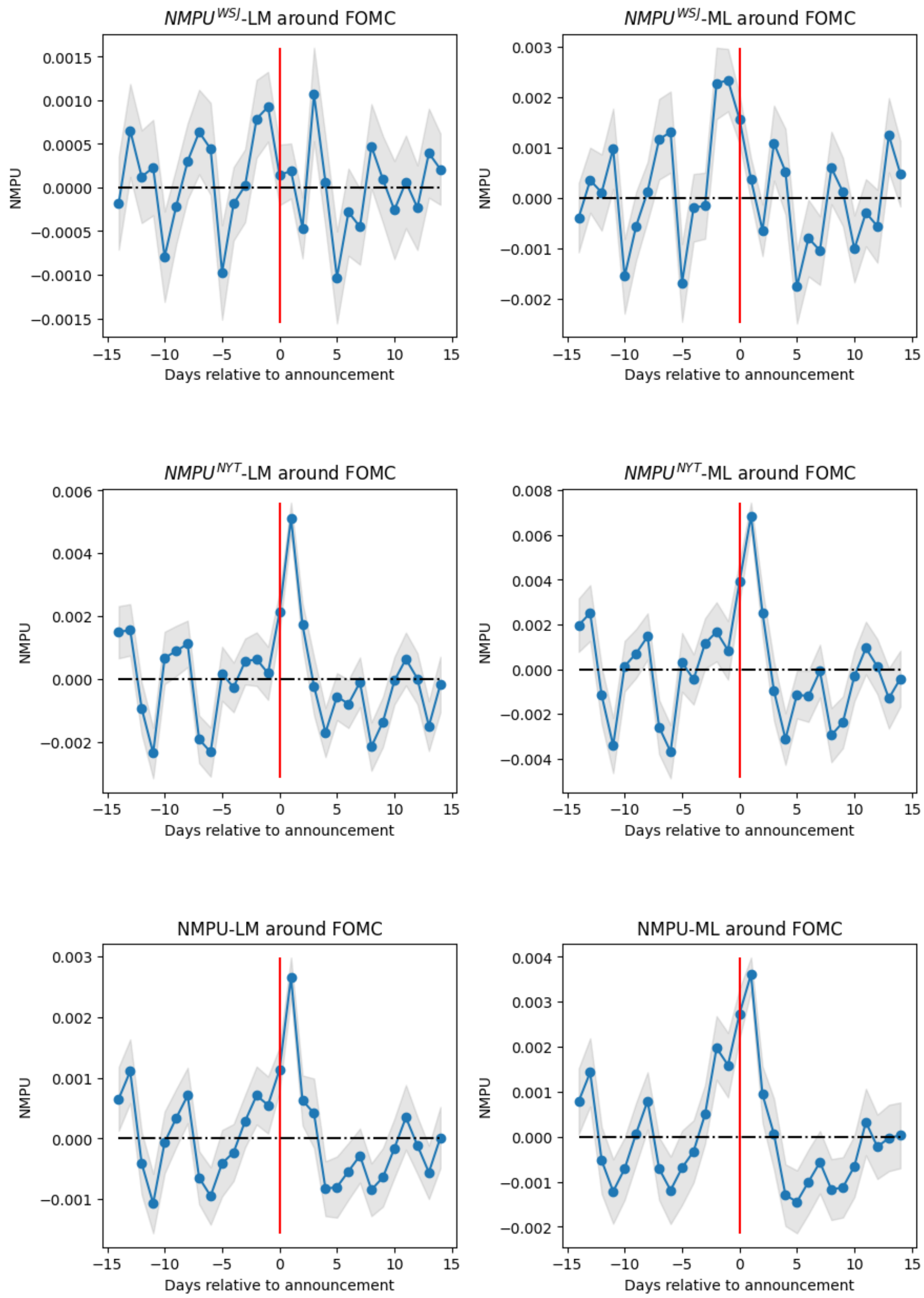

Figure 3: US cumulative NMPU after FOMC meetings

The top two figures show the average US cumulative NMPU from WSJ and NYT after FOMC meetings, detrended by the NMPU on the day before the FOMC announcement, starting at Feb 04, 1994. The red line shows the evolution of NMPU following bad news on the announcement day, where Ret $<$ 0. The blue line shows the evolution of NMPU following good news on the announcement day, where Ret $>$ 0. The bottom two figures show the difference between the blue and red line, with 95% confidence intervals.

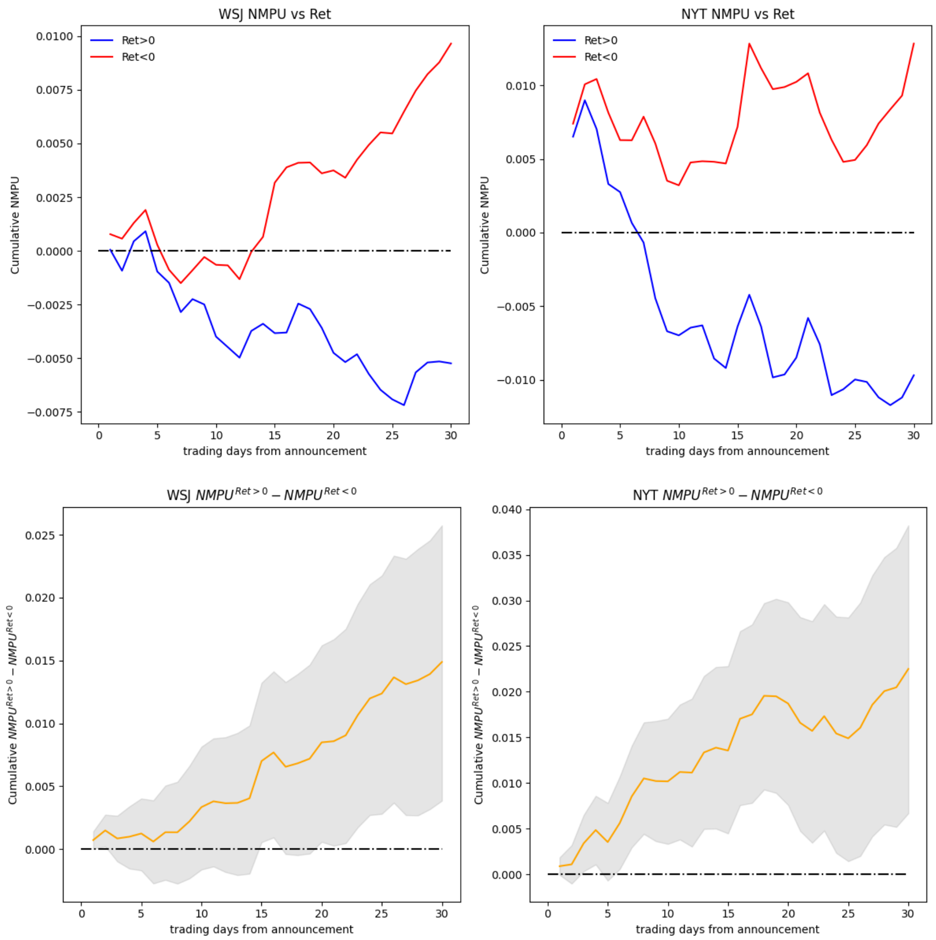

Table 1: Correlation

Panel A of this table reports the daily correlation between NMPU obtained from Wall Street Journal ($NMPU^{WSJ}$), NMPU obtained from New York Times ($NMPU^{NYT}$), and the EPU, Market-Based MPU (MPU-MKT), VIX, MOVE indices. Panel B reports the monthly correlation. The indices are all detrended by 252 day average. The monthly indices $NMPU^{WSJ}$, $NMPU^{NYT}$ and MPU-MKT are averaged across trading days within a month. The monthly VIX and MOVE are taken as the last available index in the month.

Panel A. Daily

	$NMPU^{WSJ}$	$NMPU^{NYT}$	EPU	MPU-MKT	VIX	MOVE
$NMPU^{WSJ}$	1.000	0.128	0.031	-0.007	-0.021	-0.017
$NMPU^{NYT}$	0.128	1.000	0.042	0.006	0.017	0.018
EPU	0.031	0.042	1.000	0.004	0.372	0.101
MPU-MKT	-0.007	0.006	0.004	1.000	0.308	0.124
VIX	-0.021	0.017	0.372	0.308	1.000	0.321
MOVE	-0.017	0.018	0.101	0.124	0.321	1.000

Panel B. Monthly

	$NMPU^{WSJ}$	$NMPU^{NYT}$	EPU	MPU-MKT	VIX	MOVE
$NMPU^{WSJ}$	1.000	0.110	0.286	-0.552	-0.023	-0.219
$NMPU^{NYT}$	0.110	1.000	0.252	-0.082	0.026	-0.120
EPU	0.286	0.252	1.000	-0.316	0.425	-0.046
MPU-MKT	-0.552	-0.082	-0.316	1.000	0.183	0.787
VIX	-0.023	0.026	0.425	0.183	1.000	0.623
MOVE	-0.219	-0.120	-0.046	0.787	0.623	1.000

Table 2: Uncertainty changes around announcements

This table reports the results of the following regressions:

$$
\begin{aligned}
\mathrm{NMPU}_{\tau,[1,3]} =& \alpha + \beta_1 \mathbb{1}_{\mathrm{Ret}_\tau<0} + \epsilon_\tau, \\
\mathrm{NMPU}_{\tau,[1,3]} =& \alpha + \beta_1 \mathrm{Ret}_\tau + \beta_2 |\mathrm{Ret}_\tau| + \epsilon_\tau, \\
\Delta\mathrm{NMPU}_{\tau,[-3,3]} =& \alpha + \beta_1 \mathbb{1}_{\mathrm{Ret}_\tau<0} + \epsilon_\tau \text{ and} \\
\Delta\mathrm{NMPU}_{\tau,[-3,3]} =& \alpha + \beta_1 \mathrm{Ret}_\tau + \beta_2 |\mathrm{Ret}_\tau| + \epsilon_\tau,
\end{aligned}
$$

where $\mathbb{1}_{\mathrm{Ret}_\tau<0}$ is 1 if $\mathrm{Ret}_\tau < 0$ and 0 otherwise. We look at 223 FOMC announcements starting at Feb 4, 1994. The daily EPU, MPU-MKT and VIX are also trading day only and detrended by 252 day average. The definitions of EPU, ΔEPU, MPU and ΔMPU are the same as NMPU and ΔNMPU, following the variable definitions in the formula. For VIX, the variable definitions are $\mathrm{VIX}_{\tau,[1,3]} = \mathrm{VIX}_{\tau+3} - \mathrm{VIX}_{\tau+1}$, $\Delta\mathrm{VIX}_{\tau,[-3,3]} = \mathrm{VIX}_{\tau+3} - \mathrm{VIX}_{\tau-3}$. The robust standard errors HC3 are reported in parenthesis. *, **, *** denote the statistical significance at the 10%, 5%, 1% levels, respectively.

Panel A. NMPU

	WSJ				NYT				Combined			
	NMPU		ΔNMPU		NMPU		ΔNMPU		NMPU		ΔNMPU	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$\mathbb{1}_{\mathrm{Ret}_\tau<0}$	0.0003		0.0007		0.0011*		0.0000		0.0007*		0.0004	
	(0.00)		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)	
Ret_τ		-0.0392**		-0.0642**		-0.0802**		-0.0654		-0.0597***		-0.0648**
		(0.02)		(0.03)		(0.03)		(0.04)		(0.02)		(0.03)
$\lvert\mathrm{Ret}_\tau\rvert$		-0.0145		0.0145		0.0419		0.0178		0.0137		0.0162
		(0.03)		(0.04)		(0.05)		(0.06)		(0.03)		(0.04)
Intercept	0.0001	0.0005*	-0.0015***	-0.0012***	0.0023***	0.0027***	0.0016***	0.0016**	0.0012***	0.0016***	0.0000	0.0002
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
R^2	-0.002	0.023	0.004	0.025	0.009	0.019	-0.005	0.002	0.009	0.034	-0.002	0.019
N	223	223	223	223	223	223	223	223	223	223	223	223

Panel B. Existing Measures

	EPU				MPU-MKT				VIX			
	EPU		ΔEPU		MPU		ΔMPU		VIX		ΔVIX	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$\mathbb{1}_{\mathrm{Ret}_\tau<0}$	-12.7573*		-7.2418		0.0122		0.0169***		-0.6314*		0.6390	
	(7.21)		(6.32)		(0.02)		(0.01)		(0.33)		(0.55)	
Ret_τ		606.1612		295.7977		-1.6229		-1.1311***		23.8529		-64.3195
		(461.19)		(419.98)		(1.12)		(0.35)		(18.51)		(39.26)
$\lvert\mathrm{Ret}_\tau\rvert$		1017.0459*		-46.9111		-0.3716		-0.4200		-75.0089***		-11.3744
		(617.92)		(549.83)		(1.56)		(0.59)		(28.48)		(53.21)
Intercept	15.1899***	-0.2255	10.2654**	6.7469	-0.0353***	-0.0227	-0.0244***	-0.0106**	0.3260	0.6042**	-0.3357	0.2030
	(5.64)	(4.77)	(4.42)	(4.41)	(0.01)	(0.01)	(0.00)	(0.00)	(0.25)	(0.28)	(0.33)	(0.39)
R^2	0.008	0.043	0.001	-0.005	-0.003	0.009	0.028	0.088	0.011	0.038	0.002	0.028
N	223	223	223	223	223	223	223	223	223	223	223	223

Table 3: Uncertainty with Fundamentals

This table reports the results of the following regression:

$$y_t = \alpha + \beta_1 F_t^{M-Q} + \beta_2 F_t^{Q-Y} + \beta_3 F_t^{Y-4Y} + \beta_4 |F_t^{M-Q}| + \beta_5 |F_t^{Q-Y}| + \beta_6 |F_t^{Y-4Y}| + \epsilon_t,$$

where $y_t = \text{NMPU}_t$ in Panel A and $y_t = \text{MPU-MKT}_t$ in Panel B. The MPU-MKT is also the monthly average of trading day values. The definitions of F can be found in Section 4. The standard errors are calculated using Newy-west (HAC) with max lags set to $N^{\frac{1}{4}}$. The fundamental indices are scaled down by a factor of 100 in both regressions.

Panel A. NMPU

	Housing (1)	CPI (2)	Unemployment (3)	Fed Fund (4)	Treasury Bond (10y) (5)
F_t^{M-Q}	0.0239	-0.0090	0.0403	0.0275	-0.0372
	(0.02)	(0.02)	(0.03)	(0.08)	(0.05)
F_t^{Q-Y}	-0.0009	0.0044	-0.1025***	0.0263	0.0516*
	(0.01)	(0.00)	(0.04)	(0.03)	(0.03)
F_t^{Y-4Y}	-0.0039**	-0.0132***	-0.0279*	-0.0153	0.0429
	(0.00)	(0.00)	(0.02)	(0.01)	(0.03)
$\|F_t^{M-Q}\|$	0.0135	0.0310	-0.0734	-0.0728	-0.0442
	(0.02)	(0.02)	(0.05)	(0.09)	(0.07)
$\|F_t^{Q-Y}\|$	0.0046	0.0528***	0.1835***	-0.0395	0.0153
	(0.01)	(0.01)	(0.05)	(0.04)	(0.04)
$\|F_t^{Y-4Y}\|$	0.0093***	-0.0132***	0.0823***	-0.0224	0.0861**
	(0.00)	(0.00)	(0.02)	(0.02)	(0.04)
Intercept	0.0143***	0.0161***	0.0142***	0.0159***	0.0153***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
R^2	0.191	0.089	0.095	0.025	0.018
N	387	464	440	441	466

Panel B. MPU-MKT

	Housing (1)	CPI (2)	Unemployment (3)	Fed Fund (4)	Treasury Bond (10y) (5)
F_t^{M-Q}	-2.9593	1.1934	13.6536**	19.7738	-2.6874
	(3.28)	(5.80)	(6.10)	(28.45)	(9.69)
F_t^{Q-Y}	-2.1240*	1.2559	34.4241**	-2.4955	8.8908
	(1.22)	(1.23)	(14.68)	(11.35)	(8.60)
F_t^{Y-4Y}	0.0973	2.7754***	14.1548***	-1.8300	-8.7707
	(0.42)	(0.95)	(3.71)	(2.83)	(12.93)
$\|F_t^{M-Q}\|$	-4.0780	-11.3145	-25.3535***	55.0558**	59.1808***
	(4.18)	(7.63)	(7.87)	(26.87)	(15.85)
$\|F_t^{Q-Y}\|$	-0.2229	-1.0564	-36.8630**	21.0834*	33.4872**
	(1.26)	(3.29)	(16.05)	(11.39)	(13.90)
$\|F_t^{Y-4Y}\|$	-1.2753**	2.7754***	-17.3927***	16.9889***	-0.2458
	(0.52)	(0.95)	(5.05)	(3.42)	(15.59)
Intercept	1.1080***	0.5891***	1.1979***	0.5851***	0.6843***
	(0.06)	(0.12)	(0.04)	(0.05)	(0.07)
R^2	0.201	0.064	0.342	0.392	0.112
N	358	369	369	369	369

Appendix

Table A1: Search words

This table reports search words to select articles related to monetary policy and national banks in the Wall Street Journal (WSJ), the New York Times (NYT) and National Post to construct the narrative monetary policy uncertainty indices (NMPU) for the US and CA. We retrieve the articles for which the search words appear either in the headline or in the article.

Country	Newspapers search words
US	("monetary policy" OR "monetary policies" OR "interest rate" OR "interest rates" OR "Federal fund rate" OR "Federal funds rate" OR "Fed fund rate" OR "Fed funds rate") AND ("Federal Reserve" OR "the Fed" OR "Federal Open Market Committee" OR "FOMC")
CA	("monetary policy" OR "monetary policies" OR "interest rate" OR "interest rates") AND ("Bank of Canada" OR "BoC")

Figure A1: US NMPU, compared with MPU and HRS MPU

This figure shows the monthly US NMPU with MPU, HRS MPU from Jan, 1984. All the scores are smoothed by a 12 month moving average. The gray vertical bars are NBER recessions.

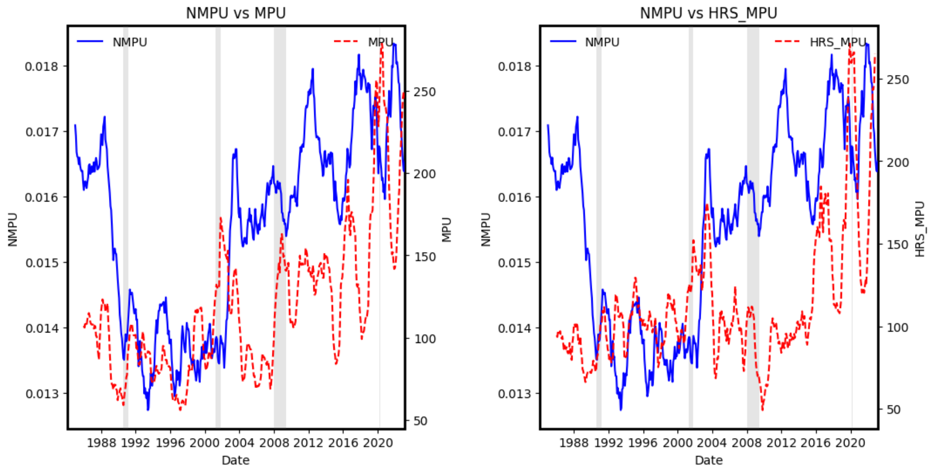

Table A2: US monthly correlation with MPU

This table adds monthly MPU and HRS MPU as compared to Table 1.

	$NMPU^{WSJ}$	$NMPU^{NYT}$	EPU	MPU-MKT	VIX	MOVE	MPU	HRS MPU
$NMPU^{WSJ}$	1.000	0.110	0.286	-0.552	-0.023	-0.219	0.322	0.200
$NMPU^{NYT}$	0.110	1.000	0.252	-0.082	0.026	-0.120	0.172	0.184
EPU	0.286	0.252	1.000	-0.316	0.425	-0.046	0.790	0.488
MPU-MKT	-0.552	-0.082	-0.316	1.000	0.183	0.787	-0.301	-0.175
VIX	-0.023	0.026	0.425	0.183	1.000	0.623	0.369	0.106
MOVE	-0.219	-0.120	-0.046	0.787	0.623	1.000	0.098	-0.077
MPU	0.322	0.172	0.790	-0.301	0.369	0.098	1.000	0.712
HRS MPU	0.200	0.184	0.488	-0.175	0.106	-0.077	0.712	1.000

Table A3: Uncertainty changes around announcements

This table reports the results of the following regressions:

$$\begin{aligned}\text{NMPU}_{\tau,[1,3]} &= \alpha + \beta_1 \text{Ret}_\tau + \epsilon_\tau \text{ and} \\ \Delta\text{NMPU}_{\tau,[-3,3]} &= \alpha + \beta_1 \text{Ret}_\tau + \epsilon_\tau.\end{aligned}$$

The Ret variable is calculated as the log return of S&P500 on the announcement day. We look at 223 FOMC announcements starting at Feb 4, 1994. The daily EPU, MPU-MKT and VIX are also trading day only and detrended by 252 day average. The definitions of EPU, ΔEPU, MPU and ΔMPU are the same as NMPU and ΔNMPU, following the variable definitions in the formula. For VIX, the variable definitions are $\text{VIX}_{\tau,[1,3]} = \text{VIX}_{\tau+3} - \text{VIX}_{\tau+1}$, $\Delta\text{VIX}_{\tau,[-3,3]} = \text{VIX}_{\tau+3} - \text{VIX}_{\tau-3}$. The robust standard errors HC3 are reported in parenthesis. *, **, *** denote the statistical significance at the 10%, 5%, 1% levels, respectively. We see that LM is not showing significance for any of the regression, thus it is not included in our main analysis.

Panel A. NMPU-LM

	WSJ		NYT		Combined	
	NMPU	ΔNMPU	NMPU	ΔNMPU	NMPU	ΔNMPU
	(1)	(2)	(3)	(4)	(5)	(6)
Ret_τ	-0.0109	-0.0100	-0.0263	-0.0364	-0.0186	-0.0232
	(0.01)	(0.02)	(0.03)	(0.03)	(0.02)	(0.02)
Intercept	0.0003**	-0.0003	0.0023***	0.0018***	0.0013***	0.0008***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
R^2	-0.000	-0.003	0.002	0.003	0.004	0.003
N	223	223	223	223	223	223

Panel B. NMPU-ML

	WSJ		NYT		Combined	
	NMPU	ΔNMPU	NMPU	ΔNMPU	NMPU	ΔNMPU
	(1)	(2)	(3)	(4)	(5)	(6)
Ret_τ	-0.0436***	-0.0597***	-0.0672**	-0.0599	-0.0554***	-0.0598**
	(0.02)	(0.02)	(0.03)	(0.04)	(0.02)	(0.03)
Intercept	0.0004**	-0.0011***	0.0030***	0.0017***	0.0017***	0.0003
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
R^2	0.026	0.028	0.020	0.006	0.037	0.023
N	223	223	223	223	223	223

Panel C. Existing measures

	EPU		MPU-MKT		VIX	
	EPU	ΔEPU	MPU	ΔMPU	VIX	ΔVIX
	(1)	(2)	(3)	(4)	(5)	(6)
Ret_τ	921.6324**	281.2467	-1.7382*	-1.2613***	0.5864	-67.8477**
	(441.31)	(328.18)	(1.00)	(0.44)	(20.91)	(32.89)
Intercept	7.2536**	6.4019*	-0.0254**	-0.0137***	0.0526	0.1193
	(3.61)	(3.31)	(0.01)	(0.00)	(0.18)	(0.30)
R^2	0.030	-0.000	0.013	0.088	-0.005	0.032
N	223	223	223	223	223	223

Table A4: Uncertainty with Fundamentals Shifted

This table reports the results of the following regression:

$$y_t = \alpha + \beta_1 F_{t-1}^{M-Q} + \beta_2 F_{t-1}^{Q-Y} + \beta_3 F_{t-1}^{Y-4Y} + \beta_4 |F_{t-1}^{M-Q}| + \beta_5 |F_{t-1}^{Q-Y}| + \beta_6 |F_{t-1}^{Y-4Y}| + \epsilon_t,$$

where $y_t = \text{NMPU}_t$ in Panel A and $y_t = \text{MPU-MKT}_t$ in Panel B. This is the same regression as in Table 3, but we shift the fundamentals by 1 month to account for the announcement delay (F_{t-1} is reported in month t).

Panel A. NMPU

	Housing (1)	CPI (2)	Unemployment (3)	Fed Fund (4)	Treasury Bond (10y) (5)
F_{t-1}^{M-Q}	0.0402***	-0.0151	0.0284	0.0890	-0.0138
	(0.02)	(0.03)	(0.03)	(0.08)	(0.05)
F_{t-1}^{Q-Y}	-0.0073	0.0055	-0.1410***	0.0092	0.0512
	(0.01)	(0.01)	(0.05)	(0.03)	(0.03)
F_{t-1}^{Y-4Y}	-0.0031	-0.0150***	-0.0184	-0.0139	0.0431
	(0.00)	(0.00)	(0.02)	(0.01)	(0.04)
$\|F_{t-1}^{M-Q}\|$	0.0240	0.0902***	0.0769**	0.0453	-0.0498
	(0.02)	(0.03)	(0.04)	(0.09)	(0.06)
$\|F_{t-1}^{Q-Y}\|$	0.0024	0.0434***	0.1489***	-0.0587	0.0041
	(0.01)	(0.01)	(0.05)	(0.04)	(0.05)
$\|F_{t-1}^{Y-4Y}\|$	0.0096***	-0.0150***	0.0841***	-0.0206	0.0902**
	(0.00)	(0.00)	(0.02)	(0.02)	(0.04)
Intercept	0.0143***	0.0162***	0.0141***	0.0159***	0.0154***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
R^2	0.218	0.109	0.111	0.020	0.018
N	386	463	439	440	465

Panel B. MPU-MKT

	Housing (1)	CPI (2)	Unemployment (3)	Fed Fund (4)	Treasury Bond (10y) (5)
F_{t-1}^{M-Q}	-1.9253	3.6503	13.4730**	21.1984	6.7612
	(3.24)	(5.34)	(5.61)	(29.76)	(9.78)
F_{t-1}^{Q-Y}	-2.4740**	1.1266	37.0900**	-3.5445	7.2327
	(1.21)	(1.22)	(14.77)	(11.22)	(8.53)
F_{t-1}^{Y-4Y}	0.1823	2.9844***	13.5827***	-1.4348	-5.6672
	(0.42)	(0.95)	(3.67)	(2.70)	(12.72)
$\|F_{t-1}^{M-Q}\|$	-4.6787	-14.6431**	-25.7737***	55.5720*	69.6054***
	(4.07)	(6.84)	(7.38)	(28.93)	(16.04)
$\|F_{t-1}^{Q-Y}\|$	-0.0615	-0.7754	-38.9876**	21.7277*	33.2328**
	(1.25)	(3.30)	(16.14)	(11.40)	(13.52)
$\|F_{t-1}^{Y-4Y}\|$	-1.3402**	2.9844***	-17.4062***	16.8733***	3.9768
	(0.53)	(0.95)	(5.16)	(3.36)	(15.45)
Intercept	1.1097***	0.5671***	1.2033***	0.5833***	0.6601***
	(0.06)	(0.12)	(0.04)	(0.05)	(0.07)
R^2	0.201	0.081	0.348	0.394	0.129
N	357	369	369	369	369

Figure A2: CA NMPU, compared with EPU

This figure shows the monthly Canadian NMPU with EPU from Jan, 1984. Note that the NMPU here is a simple monthly average over National Post. Both the scores are smoothed by a 12 month moving average. The gray vertical bars are NBER recessions.

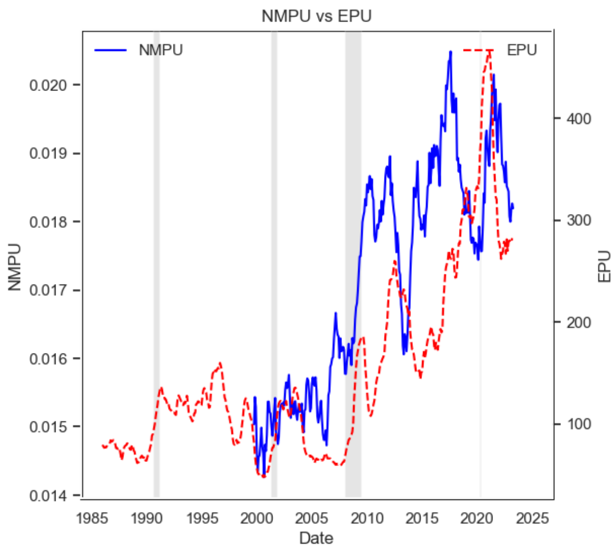

Figure A3: CA NMPU around BoC FAD

This figure shows the average Canadian NMPU from National Post, using Loughran McDonald (LM) and Machine Learning (ML) scores, around BoC FAD (fixed announcement date), starting at Aug 28, 2001. For this plot only, the Canadian NMPU is detrended by a 252 day trailing average.

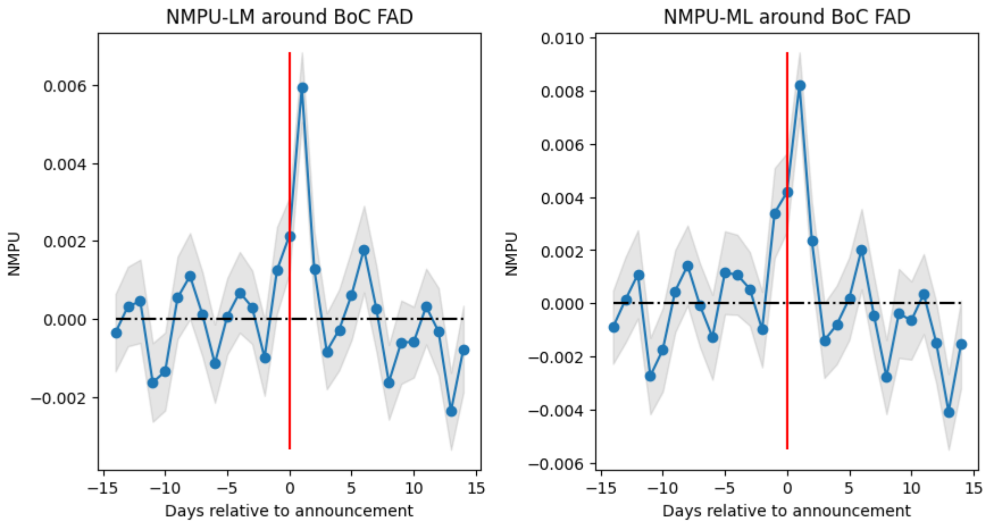

Table A5: Uncertainty changes around announcements (CA)

This table reports the results of the following regressions for Canadian market:

$$
\begin{aligned}
\mathrm{NMPU}_{\tau,[1,3]} &= \alpha + \beta_1 \mathrm{Ret}_\tau + \epsilon_\tau, \\
\mathrm{NMPU}_{\tau,[1,3]} &= \alpha + \beta_1 \mathbb{1}_{\mathrm{Ret}_\tau<0} + \epsilon_\tau, \\
\mathrm{NMPU}_{\tau,[1,3]} &= \alpha + \beta_1 \mathrm{Ret}_\tau + \beta_2 |\mathrm{Ret}_\tau| + \epsilon_\tau, \\
\Delta\mathrm{NMPU}_{\tau,[-3,3]} &= \alpha + \beta_1 \mathrm{Ret}_\tau + \epsilon_\tau, \\
\Delta\mathrm{NMPU}_{\tau,[-3,3]} &= \alpha + \beta_1 \mathbb{1}_{\mathrm{Ret}_\tau<0} + \epsilon_\tau \text{ and} \\
\Delta\mathrm{NMPU}_{\tau,[-3,3]} &= \alpha + \beta_1 \mathrm{Ret}_\tau + \beta_2 |\mathrm{Ret}_\tau| + \epsilon_\tau,
\end{aligned}
$$

where $\mathbb{1}_{\mathrm{Ret}_\tau<0}$ is 1 if $\mathrm{Ret}_\tau < 0$ and 0 otherwise. The Ret is calculated as the log return of TSX on the announcement day. We look at BoC announcements starting at Aug 28, 2001. Some datapoints are removed due to lack of news around the announcement. We don't exclude non-trading days nor detrend the Canadian data as the stock return behavior of Canadian market is not yet well studied and the daily coverage of news is lower. The robust standard errors HC3 are reported in parenthesis. *, **, *** denote the statistical significance at the 10%, 5%, 1% levels, respectively.

	NMPU			ΔNMPU		
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}_{\mathrm{Ret}_\tau<0}$		-0.0001			0.0008	
		(0.00)			(0.00)	
Ret_τ	-0.0539		-0.0494	-0.1176**		-0.1096**
	(0.04)		(0.04)	(0.05)		(0.05)
$\lvert\mathrm{Ret}_\tau\rvert$			-0.0526			-0.0727
			(0.05)			(0.05)
Intercept	0.0182***	0.0183***	0.0187***	-0.0003	-0.0007	0.0003
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
R^2	0.009	-0.006	0.013	0.029	-0.005	0.030
N	175	175	175	144	144	144

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