Measuring Inflation Uncertainty *

Viral V. Acharya[†1], Sebastian Hillenbrand[‡2], and Venky Venkateswaran[§3]

[1]NYU Stern School of Business, CEPR, ECGI and NBER
[2]Harvard Business School
[3]NYU Stern School of Business and NBER

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PRELIMINARY: DO NOT CIRCULATE

Abstract

Inflation uncertainty plays a central role in understanding macroeconomic uncertainty as well as in modeling interest rate volatility and term premia in fixed income markets. However, reliable empirical measures of inflation uncertainty are no longer directly available for the United States (US) due to the (inexplicable) lack of adequate trading in inflation-linked options since the end of 2017. We fill this gap by providing two sets of measures of inflation uncertainty. The first set is based on textual analysis of news articles performed using a Large Language Model. The second set uses market-based information and comprises two approaches. One employs a machine-learning algorithm trained on the period from 2011 to 2017 when inflation-linked options provided a direct and real-time measure. It predicts inflation uncertainty over multiple horizons using a combination of predictor variables including inflation swaps, interest rate options (caps and floors), and implied volatility measures for commodities, which are all available at a high frequency. The other approach to a market-based measure extracts an implied volatility estimate from options on bond ETFs. We compare our measures to other economic uncertainty measures as well as to survey data. As an application, we use the measures to study the drivers of inflation uncertainty in the Covid era and to document structural shifts in the evolution of interest-rate uncertainty relative to inflation uncertainty.

Keywords: Inflation expectations, inflation swaps, Large Language Models, machine learning, interest rate options, caps and floors.

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[†]vva1@stern.nyu.edu
[‡]shillenbrand@hbs.edu
[§]vvenkate@gmail.com

1 Introduction

Uncertainty of inflation, and of consumer price inflation (CPI) in particular, plays a central role in understanding macroeconomic uncertainty as well as in modeling interest rate volatility and term premia in fixed income markets. In turn, it affects consumption decisions and also financial and real investments in the economy. Inflation uncertainty is also directly linked to price stability, the key goal of monetary policy: excessively high uncertainty could indicate that the central bank may not be successful at insulating the economy from future inflationary or deflationary shocks. Despite such economic importance and policy relevance, inflation uncertainty has not been studied that extensively in the economics and finance literature. This is in part due to the lack of reliable measures. In the US, for example, liquidity in inflation options markets has – somewhat inexplicably – declined sharply since the end of 2017, eliminating a direct market-based measure.

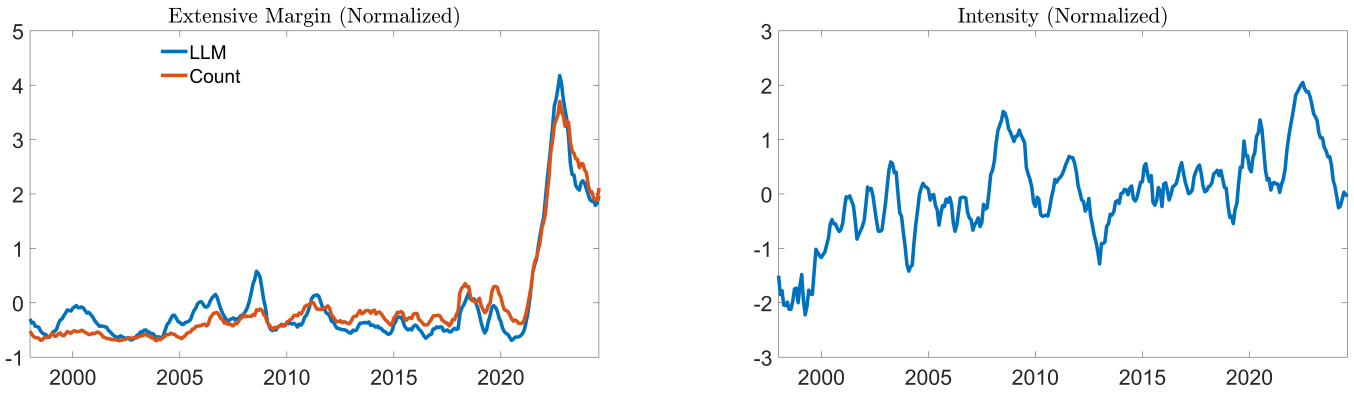
In this paper, we fill this gap by constructing new measures of inflation uncertainty using a variety of sources and approaches. We develop two sets of measures, test them against availabe benchmarks from historical market data or consumer surveys, and provide applications that illustrate their usefulness in shedding novel insights on drivers of inflation uncertainty and its relationship to interest rate uncertainty.

The first set of measures is based on a textual analysis of news articles with the help of advanced Large Language Models (LLMs).[1] Specifically, we use ChatGPT, perhaps the most widely known LLM, to analyze the text of articles from sections of the New York Times related to business, money and finance. We use ChatGPT to develop two metrics of inflation uncertainty, intended to capture extensive and intensive margins respectively. For the former, we ask the LLM to assess whether an article makes a direct reference to inflation uncertainty. The fraction of such articles in a given time period forms our extensive margin measure (see Figure 1, left panel). For the intensive margin, we ask ChatGPT to assign a numerical score (from 1-100) to each article (that contains words related to both inflation and uncertainty) based on the degree of uncertainty about inflation expressed in it, with 1 denoting a high degree of stability and 100 a high degree of uncertainty. We average the scores for such articles in a given period to obtain the intensive margin uncertainty measure (see Figure 1, right panel). The graphs show a large increase in uncertainty during the post-Covid inflationary surge, which has not dissipated entirely by the end of our sample (Aug 2024). This is particularly striking in the extensive margin series

[1] LLMs are artificial intelligence models, specifically designed to understand and process human languages using deep learning techniques (in particular, neutral networks). They are trained on a vast corpus of data from diverse sources. Their ability to generate coherent text and mimic human-like responses has made them extremely popular and influential in a number of areas. Their use in the academic literature in finance and economics literature is growing though still nascent – for a few recent examples, see Bybee (2023), Faria-e Castro and Leibovici (2024) and Lopez-Lira and Tang (2023).

in the left panel.

Figure 1: News-Based Measures of Inflation Uncertainty

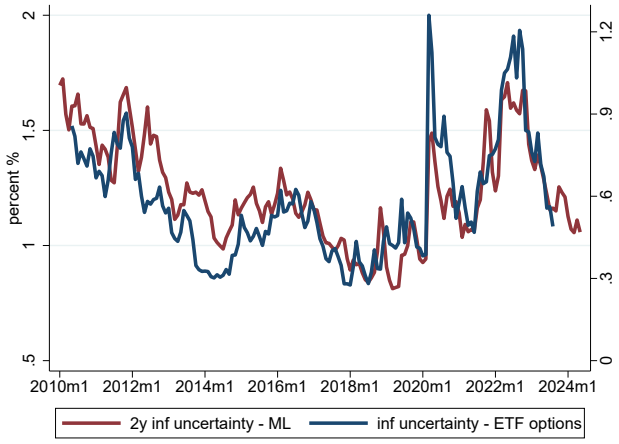


Note: The LLM line in the left panel shows a rolling 6-month moving average of business-related articles flagged by the LLM as pertaining directly to inflation uncertainty, normalized to have zero mean and unit standard deviation over the whole sample. The Count measure shows the corresponding series for the fraction based on a "naive' count of articles which mention both inflation and uncertainty. The right panel shows a rolling 6-month moving average of the intensity score assigned by the LLM to each article. See main text for details on the prompt.

Our second set of measures is constructed from market prices of derivatives. The first such measure leverages the fact that reliable market prices of derivative securities affected by inflation uncertainty were historically or are presently available. We use data on inflation-linked options during the period when they were reliable (until 2017) to train a sophisticated machine learning (ML) model, which generates a prediction for implied volatility of inflation (at various maturities) using a number of asset prices and other indicators, including implied volatilities from commodity options, as well as the level and realized volatility of expected inflation. This measure has the advantage of being available at a high frequency, essentially at any frequency the predictor variables are available. Our second market-based measure extracts inflation uncertainty from options on exchange-traded funds (ETFs). In particular, we use implied volatilities on nominal and real bond ETFs to construct an implied inflation volatility. Figure 2 plots both these series, which exhibit remarkably similar patterns over the whole sample.

We relate the four resulting inflation uncertainty time-series to other widely-used metrics of uncertainty: (i) economic uncertainty – such as the Economic Policy Uncertainty index devised by Baker, Bloom, and Davis (2016) and the Monetary Policy Uncertainty developed by Husted, Rogers, and Sun (2020); (ii) financial market uncertainty – such as equity volatility proxied by VIX and its fixed-income counterpart MOVE; and, (iii) survey-based measures of inflation uncertainty (which are less frequently available) – such as in the Survey of Consumer Expectations and the Survey of Professional Forecasters. While all of these measures of uncertainty comove to an extent, we show that our inflation uncertainty

Figure 2: Market-based Measures of Inflation Uncertainty



Note: This figure shows two measures of inflation uncertainty, one computed using a machine learning algorithm (ML) trained on past inflation options and the other computed from options on bond ETFs. For details, see Section 3.

measures have important differences. This is true even relative to survey-based measures: our inflation uncertainty series track the survey measures at low frequency reasonably closely but also show significant high-frequency movements, likely due to their embedding of news and market data. This makes them a potentially valuable tool, both from a research and policy-making standpoint. For researchers, high frequency variation allows for interesting ways to analyze driving forces and economic mechanisms. For policy-makers, our measures provide a real-time indicator of inflation uncertainty, paralleling similar, widely-tracked uncertainty measures (for example, the VIX for equity markets).

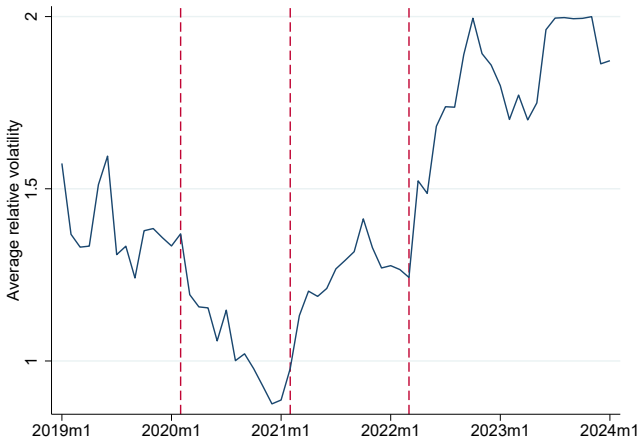
We then provide two salient applications of our inflation uncertainty measures.

First, we use the measures to shed new light on how inflation uncertainty has evolved over the post-pandemic period in terms of its underlying drivers. Using prompts in ChatGPT to decompose uncertainty drivers, we find that after the initial surge and immediate decline at pandemic's outbreak, inflation uncertainty rose steeply in 2021 driven primarily by supply chain challenges and disruptions which abated in 2022 but were then compensated by energy and commodity prices (which kept inflation uncertainty high); while both of these drivers declined in their importance in 2023, it did not bring down inflation uncertainty to pre-pandemic levels as uncertainty hovering over economic growth and consumer behavior as well as over interest rates and monetary policy picked up thereafter. This way, our LLM approach helps not only construct the inflation uncertainty measures but through a "topics" analysis, also helps understand the underlying drivers.

Second, we employ the measures to study their interaction with interest rate uncertainty (specifically, implied volatility on interest rate options) and how their relatonship has evolved over the post-

pandemic period. We document that the ratio of interest rate uncertainty to inflation uncertainty exhibits structural breaks almost every during 2020-2023 period. This relative volatility began falling in early 2020 at the onset of pandemic. It started rising in 2021, but remained below pre-Covid levels until early 2022 (when the Fed started hiking rates). Subsequently, it continued to rise and has settled at a higher level compared to the pre-pandemic benchmark. In other words, interest rate uncertainty rose significantly relative to inflation uncertainty during the post-Covid recovery and has not reverted, even as inflation has retracted most of its gains. This is an important empirical fact whose theoretical underpinnings deserve further theoretical and empirical inquiry.

Figure 3: Interest Rate Uncertainty relative to Inflation Uncertainty, 2019- .



Note: This figure shows the ratio of interest rate uncertainty (measured from options on Eurodollar futures contracts) to our market-based inflation uncertainty measure. The vertical lines mark structural breaks in a linear model estimated using the methodology of Bai and Perron (1998). For details, see Section 4.

Related literature. Our work is related to, and builds on, several strands in the literature. We speak directly to the growing body of work analyzing the post-pandemic inflation surge, both in terms of its underlying drivers as well as policy responses. An (incomplete) reading list would include Ball, Leigh, and Mishra (2022), Bernanke and Blanchard (2023), Gagliardone and Gertler (2023) and di Giovanni, Kalemli-Özcan, Silva, Yildirim, and Yildirim (2023) on the drivers of inflation and Reis (2022), Beaudry, Carter, and Lahiri (2023) and English, Forbes, and Ubide (Editors) on monetary policy actions.

While these studies focus on realized outcomes, Acharya et al. (2023), Armantier et al. (2023) and D'Acunto et al. (2022) focus on how these outcomes shaped inflation expectations, the focus being on the level rather than uncertainty.[2] Importantly, expectations matter as they affect consumer behavior, as shown in Armantier et al. (2015), Ascari et al. (2023) and Coibion et al. (2023) (with Coibion et al. (2023)

[2]Malmendier and Nagel (2016), D'Acunto et al. (2020) and Weber et al. (2022) focus more broadly,. beyond the pandemic period, on key drivers of inflation expectatons.

focusing in particular also on the effect of inflation uncertainty perceived by households), and firm behavior, as documented in Coibion et al. (2020).

On the specifics of our measures based on market data, derivatives market prices have been used to extract information about inflation beliefs in prior literature, e.g., in Fleckenstein, Longstaff, and Lustig (2017), Mertens and Williams (2021) Wright (2017), Bahaj, Czech, Ding, and Reis (2023), and Hilscher, Raviv, and Reis (2022). Recent work by Bauer, Pflueger, and Sunderam (2022), Bocola et al. (2024) and Grischenko and Wilcox (2024) uses instead panel data on professional forecasts to estimate a perceived Taylor Rule (first two papers) and tails in inflation expectations, respectively.

Overall, relative to this literature, we focus on constructing measures of inflation uncertainty, using large language models as well as market-based indices and derivatives prices, studying both the drivers of inflation uncertainty as well as relating it to interest rate uncertainty. In this regard, the spirit of our exercise and inquiry is closer to the work on economic uncertainty by Baker, Bloom, and Davis (2016), monetary policy uncertainty by Husted, Rogers, and Sun (2020), and geopolitical uncertainty by Caldara and Iacoviello (2021).

2 News-Based Measures of Inflation Uncertainty

In this section, we present our first measure of inflation uncertainty, constructed from news articles. Specifically, we use ChatGPT, a Large Language Model (LLM), to analyze the text of articles from sections of the New York Times related to business, economy and financial markets. Table 1 provides some summary statistics about the set of articles used in constructing this measure.

Number of months	320
First month	Jan 1998
Last month	Aug 2024
Total number of articles in Business Financial	242,314
Total number of articles in Business	31,427
Total number of articles in Money, Business, Financial	24,421
Total number of articles	298,162
Average number of words per article	645.6

Table 1: News-based Inflation Uncertainty: Descriptive Statistics.

We use ChatGPT to develop two metrics of inflation uncertainty, intended to capture extensive and intensive margins respectively. For the former, we ask the LLM to assess whether an article makes a direct reference to inflation uncertainty. The fraction of such articles in a given time period forms our extensive margin measure. For the intensive margin, we ask ChatGPT to assign a numerical score (from

1-100) to each article (that contains words related to both inflation and uncertainty) based on the degree of uncertainty about inflation expressed in it, with 1 denoting a high degree of stability and 100 a high degree of uncertainty. Figure 4 lists the actual prompts fed in to the LLM. We average the scores for such articles in a given period to obtain the intensive margin uncertainty measure.

Figure 4: Inflation Uncertainty: ChatGPT Prompt

Read the following news article: .

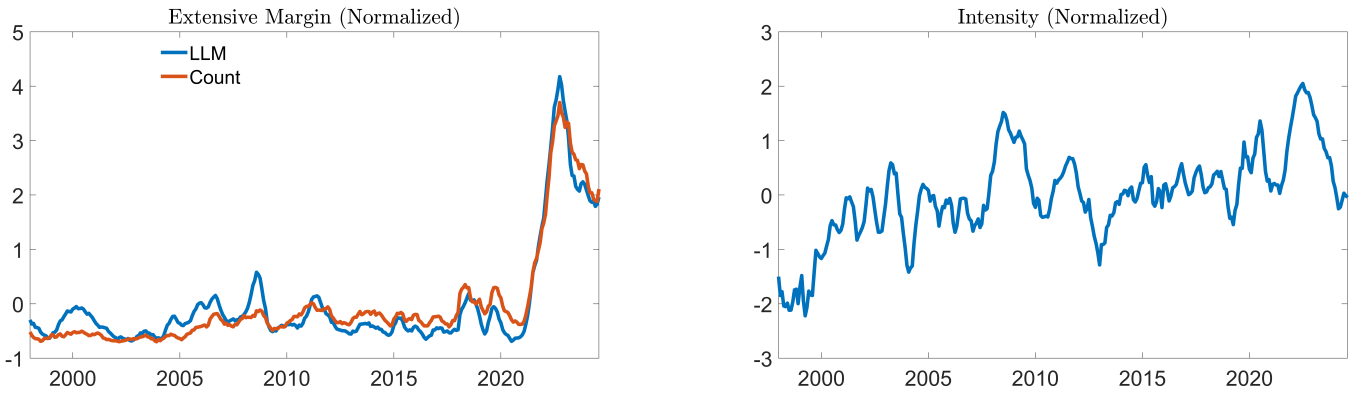
Q1: Is the article directly related to uncertainty about inflation?

Q2: If your answer to Q1 is yes, how stable/uncertain is inflation according to the article?

Answer should be a number between 1 and 100, with 1 denoting high stability and 100 denoting high uncertainty.

Model version: ChatGPT 4o Date Run: September 10, 2024

Figure 5: News-Based Measures of Inflation Uncertainty



Note: The LLM line in the left panel shows a rolling 6-month moving average of business-related articles flagged by the LLM as pertaining directly to inflation uncertainty, normalized to have zero mean and unit standard deviation over the whole sample. The Count measure shows the corresponding series for the fraction based on a "naive' count of articles which mention both inflation and uncertainty. The right panel shows a rolling 6-month moving average of the intensity score assigned by the LLM to each article. See main text for details on the prompt.

The left panel of Figure 5 reports the extensive margin measure, normalized to have zero mean and unit standard deviation. It exhibits an intuitive pattern: little inflation uncertainty for most of the sample, followed by a surge in the post-pandemic period. The peak occurred in mid-2022, when uncertainty was almost 5 standard deviations above its average level over the last 20 years. The next two years saw a downward trend, but even with that decline, uncertainty remains significantly elevated (about 2 standard deviations above the mean) relative to pre-Covid levels. For comparison, the graph also shows a "naive" measure – namely, the fraction of articles that mention both inflation and uncertainty – which displays a very similar pattern.

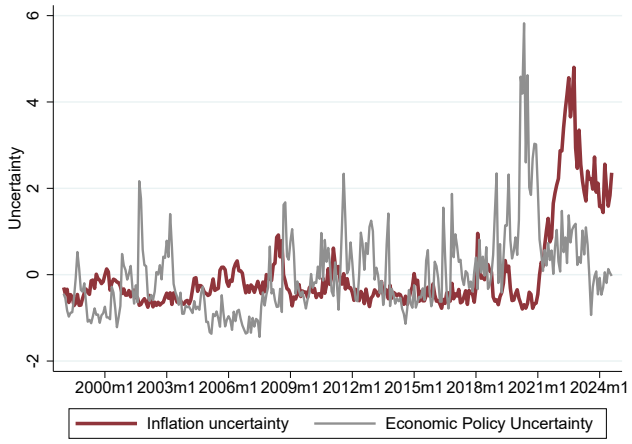
The right panel of Figure 5 shows the intensive margin measure. Perhaps unsurprisingly, this series is somewhat noisier than the extensive margin, but it also shows a run-up (and subsequent decline) in uncertainty during the post-pandemic recovery.

2.1 Comparison with other News-Based Uncertainty Measures

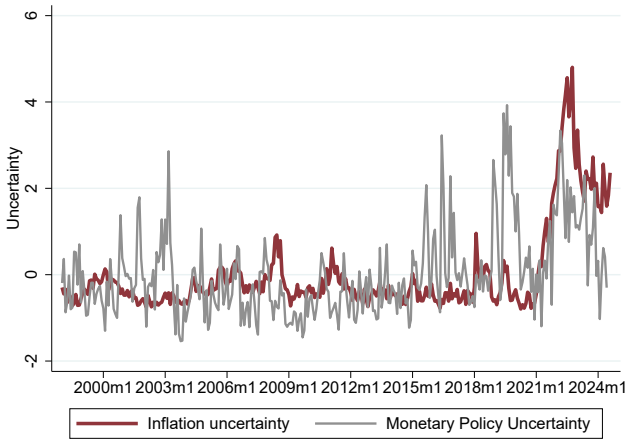
Next, we compare our inflation uncertainty series with other widely used measures of economic uncertainty. The two panels of Figure 6 plot our extensive margin inflation uncertainty measure alongside the Economic Policy Uncertainty index of Baker, Bloom, and Davis (2016) and the Monetary Policy Uncertainty index from Husted, Rogers, and Sun (2020) respectively. The graphs show that inflation uncertainty is quite distinct from policy uncertainty, even if they are periods when they comove with each other.

Figure 6: Infation uncertainty vs. Policy Uncertainty

(A) vs. Economic Policy Uncertainty



(B) vs. Monetary Policy Uncertainty



3 Marked-Based Measures of Inflation Uncertainty

3.1 Inflation Options

Inflation options in the form of zero-coupon or year-year inflation caps and floors started trading in the US after the Global Financial Crisis (GFC) and have been used to measure inflation uncertainty in prior studies (e.g., Kitsul and Wright, 2013; Fleckenstein, Longstaff, and Lustig, 2017; Mertens and Williams, 2021). However, trading volumes have decreased significantly in recent years making it impossible to get reliable transaction prices/quotes for these derivative contracts. As a result, we no longer have direct market-based measures of inflation uncertainty.

3.1.1 Predictive Machine-Learning Algorithm

Our strategy is use inflation option data for the period with relatively reliable prices: from 2010 to 2016 (following Mertens and Williams (2021)), and extend the measure beyond 2016 via a machine learning (ML) algorithm. Data on zero-coupon inflation swaps and zero-coupon inflation caps and floors are obtained from Bloomberg. We focus on the two-year, three-year and five-year maturities. For 2010-2016, we follow Kitsul and Wright (2013) and obtain the implied uncertainty for realized inflation over the different maturities.

We start by obtaining the entire distribution using the same methodology from Kitsul and Wright (2013), which involves constructing butterfly spreads for intermediate strikes and construct vertical spreads for outer strikes. The basic idea behind this approach is that – by scaling the notional appropriately – the butterfly spread around 4% gives the price of an option that pays out one dollar if future inflation equals 4%. Thus, the price of the butterfly reflects the risk-neutral probability that inflation will be equal to 4%. We then convert the prices of the butterfly and vertical spreads to probabilities imposing that the sum of the probabilities must equal one. We apply this process for both inflation and nominal interest rate options. The resulting distribution is then used to calculate a standard deviation.

Variable	Obs	Mean	Std. dev.	Min	Max
2-year inflation vol	1,644	1.30	0.24	0.86	1.90
3-year inflation vol	1,643	1.29	0.24	0.87	1.85
5-year inflation vol	1,632	1.29	0.25	0.90	1.85
2-year inflation swap level	1,611	1.65	0.37	0.69	2.72
3-year inflation swap level	1,644	1.79	0.32	1.03	2.69
5-year inflation swap level	1,644	2.00	0.33	1.20	2.72
60-day realized vol 2-year inflation swap	1,625	0.63	0.20	0.22	1.11
60-day realized vol 3-year inflation swap	1,625	0.63	0.20	0.22	1.11
60-day realized vol 5-year inflation swap	1,625	0.63	0.20	0.22	1.11
Implied volatility 2-year gold futures	1,641	0.28	0.05	0.20	0.42
Implied volatility 2-year corn futures	1,635	0.28	0.04	0.22	0.39
Implied volatility 2-year gas futures	1,641	0.35	0.03	0.27	0.43

Table 2: Descriptive Statistics.

We then use these measures to train an ML model on the period 2010-2016, and use the trained model to make predictions for inflation uncertainty starting in 2017 (out of sample). We use a number of variables for the prediction: the inflation swap rate for the same maturity, the 60-day realized volatility of the inflation swap rate as well as measures of uncertainty for commodity prices. To construct commodity price uncertainty, we obtain option data on commodity futures through CME DataMine. To capture the development of different categories of commodities such as metal, petroleum and agriculture, we focus

on three different underlyings: gold futures, oil futures, and corn futures. For every option contract, we focus on options expiring in December, since these option contracts are most frequently traded. We then use the Breeden and Litzenberger (1978) methodology to obtain the implied volatility about the future commodity price. Lastly, we interpolate between the implied volatility of December option contracts to obtain the implied volatility for a 2-year horizon. Table 2

We choose a regularized linear regression (Lasso) model and search for the optimal penalization parameter using cross-validation.[3] We estimate the model separately for 2-year, 3-year and 5-year inflation uncertainty. The estimated coefficients are summarized in Table 3.

	Horizon		
	2y	**3y**	**5y**
2-year inflation swap level	0.013		
3-year inflation swap level		0.171	
5-year inflation swap level			0.327
60-day realized vol 2-year inflation swap	0.232		
60-day realized vol 3-year inflation swap		0.382	
60-day realized vol 5-year inflation swap			0.750
Implied volatility 2-year gold futures	1.784	1.798	0.964
Implied volatility 2-year corn futures	0.707	0.000	0.000
Implied volatility 2-year gas futures	1.265	0.782	0.000
R^2	0.58	0.54	0.70
Regularization parameter (α)	0.00107	0.00160	0.00107

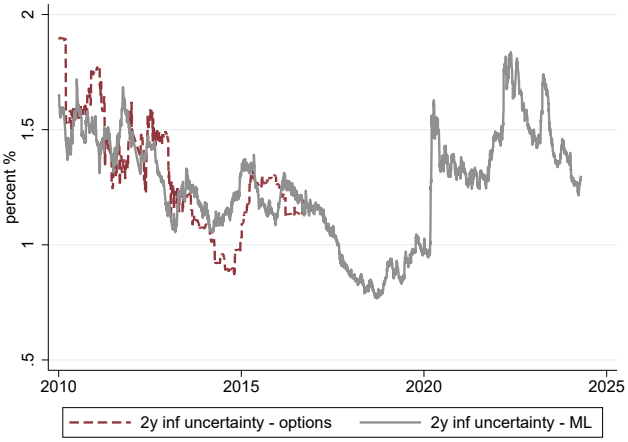
Table 3: Lasso Estimates

Figure 7 show our main measure of uncertainty about inflation over the next 2, 3, and 5 years. During 2010-2016, the ML prediction of inflation uncertainty closely tracks the option-implied inflation uncertainty which means the prediction is small in-sample. For 2017 and onwards, we rely solely on the ML prediction to measure inflation uncertainty. The figure shows that inflation uncertainty was high after the GFC – consistent with increased deflation risk (Fleckenstein, Longstaff, and Lustig, 2017) –, then stabilized at low levels between 2014-2020, and rose after the outbreak of the Covid pandemic. We zoom-in on the post-pandemic period in the next section.

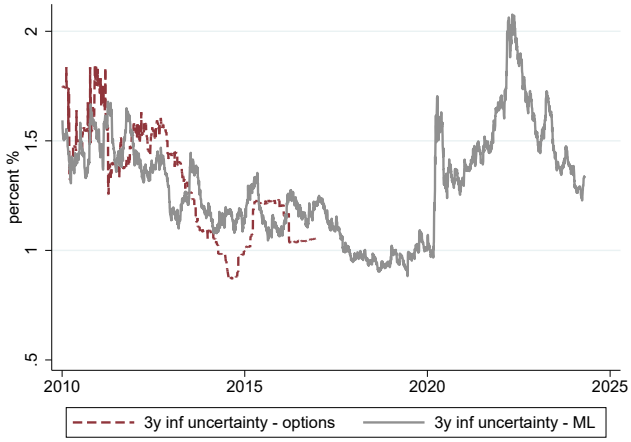
[3]Cross-validation splits the training data 2010-2016 into different pseudo in and out-of-sample data sets. More concretely, we use a 7-fold cross-validation in which the model is trained on six years of data and its performance is then evaluated on the one year not included in the training. The penalization parameter is chosen such that mean prediction error across the 7-folds is minimized.

Figure 7: Market-based Inflation Uncertainty (ML)

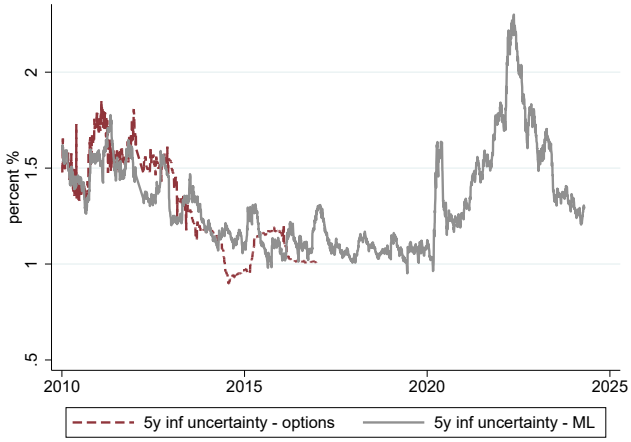
(A) 2-year inflation options



(B) 3-year inflation options



(C) 5-year inflation options



Note: Each graph shows the output of our predictive ML algorithm (grey lines) along with the training data (red).

3.2 Options on Bond ETFs

The launch and growth of bond exchange-traded funds (ETFs) provides another source of market-based information about inflation uncertainty. Though there are no ETFs investing in products directly linked to expected inflation (such as inflation swaps), we can use options on Treasury ETFs (nominal) and TIPS ETFs to construct a measure for inflation uncertainty. We provide a detailed description of this procedure in the appendix and describe only the essence of it here.

We use 3-month options on ETFs that hold either Treasuries or TIPS (with an average duration of about 7-8 years) to compute the implied volatility of nominal and real rates. To compute the implied volatility of expected inflation over 7-8 years, we need to make an assumption about the implied correlation between nominal and real rates since it is not observed. We approximate the implied correlation using the realized correlation of the underlying ETFs over the past 90 trading days.

We obtain option data on TIPS and Treasury ETFs from OptionMetrics. For TIPS ETFs, we choose as the underlying the TIPS ETF with the highest option trading volume. This is the *iShares TIPS Bond ETF* (ticker: TIP) which holds a portfolio of TIPS with a maturity of at least one year (the average duration of bonds held by the ETF is on average 7.8 years). From the set of Treasury ETFs, we then the chose the *iShares 7-10 Year Treasury Bond ETF* since it has a similar duration (its average duration is 7.7 years) and options referenced to it have a high trading volume. We obtain the at-the-money-forward (atm) (i.e., options that are at-the-money based on the forward price) implied volatilities for American calls and puts with a 3-month maturity (we use the average of the call and the put). OptionMetrics constructs these implied volatilities by first using a Cox-Ross-Rubinstein binomial tree model to compute the implied volatility for each traded option and then applies a kernel smoothing technique to obtain a volatility surface across calls/puts, maturity, strikes.

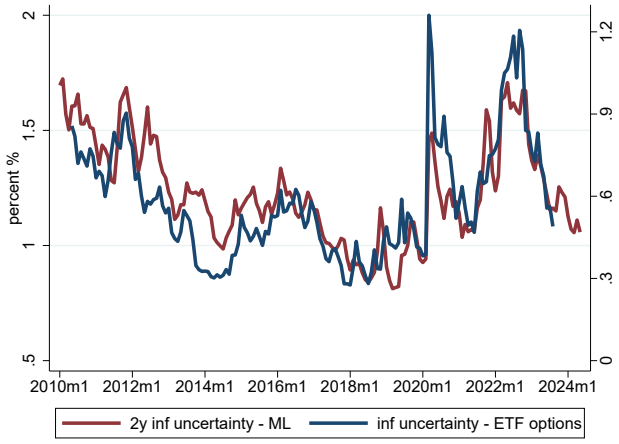
Figure 8 compares the ETF-option-implied inflation uncertainty with the other market-based measure of inflation uncertainty described in the previous subsection.[4] Despite the different approaches used, the time-series dynamics of the two measures are remarkably similar. In particular, there is a close relationship between the two variables in the out-of-sample period (2017-2024) serving as a validation of the ML prediction approach.

3.3 Comparison with Other Market-Based Uncertainty Measures

In this subsection, we compare our inflation uncertainty series to market-based measures of equity and interest rate uncertainty. In Figure 9, we plot our 5y inflation uncertainty series with VIX (left panel)

[4]Our original measure is about the uncertainty over average realized inflation over the next xx, say 3, years. The ETF vol is about the short-term (3month) uncertainty over expected inflation over the next 7 years

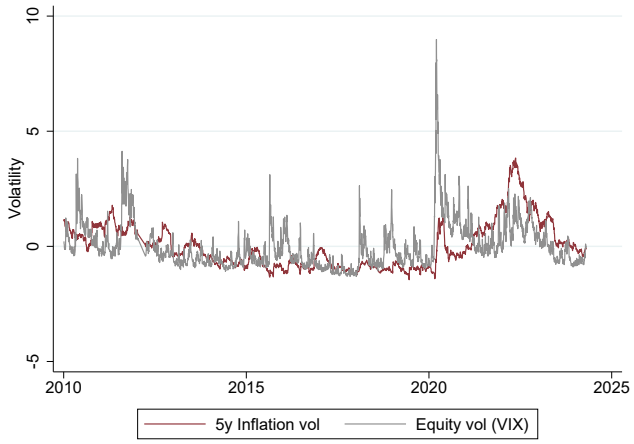
Figure 8: Market-based Inflation Uncertainty (ETF)



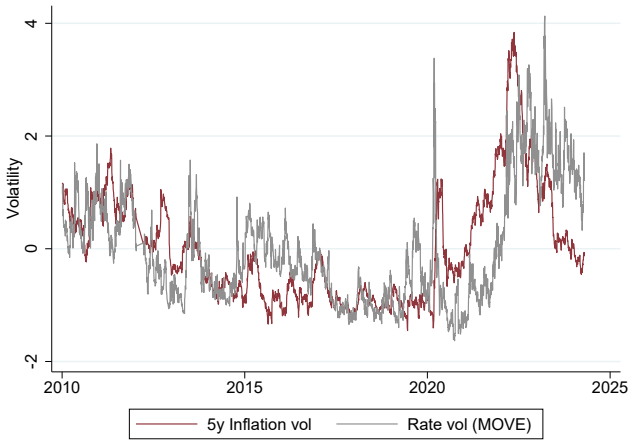
and MOVE index (right panel). The two graphs show some degree of comovement, especially during periods of stress (e.g. early 2020), but there are significant variations

Figure 9: Comparison with other Market-Based Uncertainty Measures

(A) vs. Equity Volatility (VIX)



(B) vs. Treasury Volatility (MOVE)



3.4 Comparison with Survey-Based Measures of Inflation Uncertainty

In this subsection, we compare our market-based measures with those from surveys. We use two surveys that elicit participants's views about the entire distribution of future inflation: the Survey of Professional Forecasters (SPF) and the Survey of Consumer Expectations (conducted by the New York Fed since 2013). These surveys are available at a lower frequency than the market-based measure, but help build confidence that the market-based measure is in fact a good proxy for inflation uncertainty in the economy.

Survey of Professional Forecasters. The Survey of Professional Forecasters (SPF) is conducted by the Federal Reserve Bank of Philadelphia on a quarterly basis and surveys a wide range of professional forecasters. The survey is typically conduct at the beginning of the second month of a quarter.

We obtain the mean and median forecasts for the three-month T-Bill rate, the CPI index, the PCE index and core PCE index. Similar to the SEP, the inflation forecasts correspond to the Q4:Q4 percentage change in the price level and forecasters make forecasts for the end of the next three calendar years. We interpolate between these forecasts to obtain one-year and two-year forecasts.

In addition to point forecasts, the SPF also asks for density projections for both the Q4:Q4 percentage changes in core CPI inflation (PRCCPI) and core PCE inflation (PRCPCE) for the end of the current year as well as the next year. Each respondent provides the probability that the change in core CPI "will decline", will change by "0.0% to 0.4%", "0.5% to 0.9%", "1.0% to 1.4%", "1.5% to 1.9%", "2.0% to 2.4%", "2.5% to 2.9%", "3.0% to 3.4%", "3.5% to 3.9%", or "4.0 or more". We first take compute the mean probability across all survey respondents to get the average probability for a given inflation change and then interpolate across horizons to get the distribution for inflation over the next year.

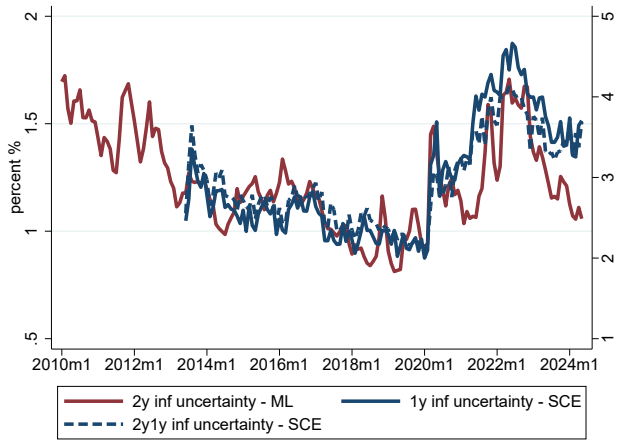
Survey of Consumer Expectations. The Survey of Consumer Expectations (SCE) conducted by the Federal Reserve Bank of New York is a nationally representative, internet-based survey of a rotating panel of approximately 1,300 household heads. We use the variables aggregate variables *inflation expectations* and *inflation uncertainty* reported on the website.

In the survey, "respondents are asked for the percent chance that, over the next 12 months, the rate of inflation (deflation) will be 12% or higher; between 8% and 12%; between 4% and 8%; between 2% and 4%; between 0 and 2%. A generalized beta distribution is fitted to the responses of each survey participant." To obtain the variable *inflation expectations* the mean of the distribution is calculated for each respondent and then the median is taken across all respondents. To obtain the variable *inflation uncertainty* the difference between the 75th and 25th percentile of each respondents' distribution is calculated and then the median is taken across all respondents. In addition to asking about inflation over the next year, the survey also respondents are asked "about inflation three-years ahead (over the twelve-month period between [current date + 2 years] and [current date + 3 years])" (we denote this as 2y1y inflation uncertainty).

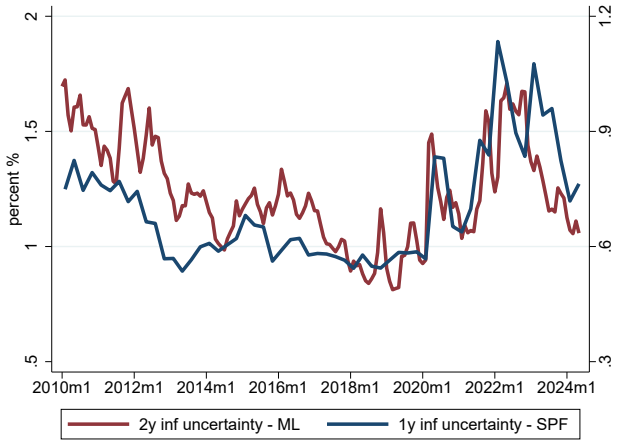
Panel (A) of Figure 10 shows a broadly similar pattern for households' perceived inflation uncertainty from the SCE compared to our market-based inflation measure. At the end of the sample, however, the two diverge somewhat – the survey evidence points to inflation uncertainty remaining stubbornly high relative to the market-based measure. Panel (B) of Figure 10 compares professional forecast-

Figure 10: Survey-Based Measures of Inflation Uncertainty

(A) Survey of Consumer Expectations



(B) Survey of Professional Forecasters



ers' perceived inflation uncertainty to the market-based proxy. Again, the broad trends over the sample are similar.

4 Application: Inflation in the Covid Era

In this section, we illustrate how our inflation uncertainty measures can be used to shed new light on the Covid era. We present two exercises – one uses the news-based measure from Section 2 to dig deeper into how the drivers of inflation uncertainty have evolved over this period, while the other compares the behavior of our market-based measure from Section 3 to comparable data on interest rate uncertainty.

4.1 Drivers of Inflation Uncertainty

For our first exercise, we ask ChatGPT to assign from Jan 2020 through 2024 to sort the key factors causing inflation uncertainty in a given article into a set of topics. The full list of topics and details of the prompt are laid out in Figure 11.

Figure 11: Inflation Drivers: ChatGPT Prompt

Can you sort the phrases in the attached file into the following phrases:

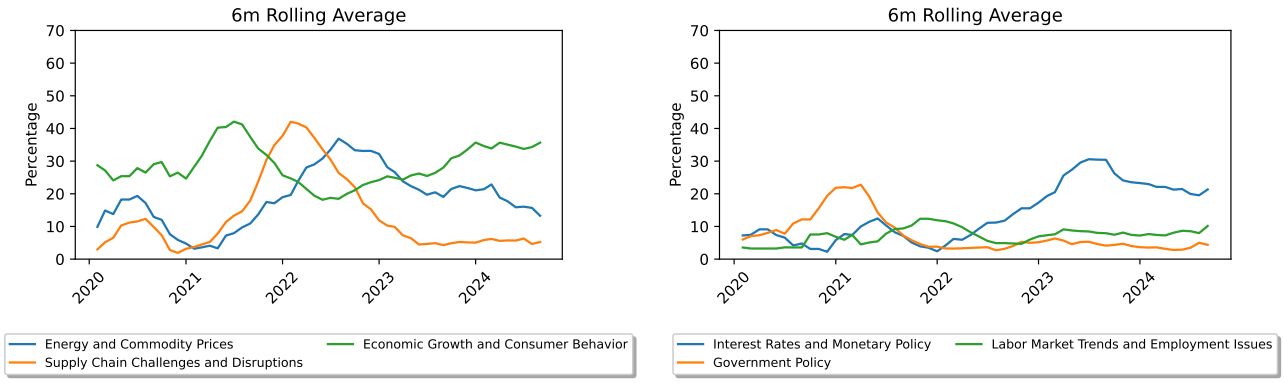
[*'Inflation and Price Dynamics ', 'Labor Market Trends and Employment Issues ', 'Economic growth and consumer behavior ', 'Currency Fluctuations and Exchange Rates ', 'Supply Chain Challenges and Disruptions ', 'Interest Rates and Monetary Policy ', 'Corporate Performance and Profitability ', 'Housing Market and Real Estate Trends ', 'Energy and Commodity Prices ', 'Financial Market Volatility and Investment Risks ', 'Government policy'*]

Model version: ChatGPT 4o Date Run: September 10, 2024

Figure 12 plots a simple measure of the relative importance of a given topic: the fraction of arti-

cles related to inflation uncertainty that is mapped to that topic by the LLM prompt in Figure 11. The left panel reveals how supply chain issues rose in importance during 2021, but have since largely dissipated. The contribution of energy and commodity prices peaked in mid-2022 (shortly after the Russian invasion of Ukraine) before declining steadily. The strength of the economic recovery and consumer spending displays the opposite pattern: it was less of an issue in 2021-22, but has since become a crucial factor behind inflation uncertainty. This is consistent with an emerging narrative about how supply-side factors played an important role in determining inflation dynamics early on in the recovery but demand-side factors emerged as the key factor – see , for example, Giannone and Primiceri (2024).

Figure 12: Drivers of Inflation Uncertainty (2020-2024)



The right panel shows the patterns for policy-related topics (as well as for labor market trends). It shows that monetary policy issues are an important contributor to inflation uncertainty today (i.e. in mid-2024). Government policy more broadly however had a role to play during the pandemic (and in the early stages of the recovery), but does not feature prominently in news stories about inflation uncertainty today.

4.2 Inflation vs Interest Rate Uncertainty

In this subsection, we compare the evolution of our market-based inflation uncertainty measure with that of interest rate uncertainty. The latter are obtained from market prices of options on nominal rates, specifically options on Eurodollar contracts at about 2-, 3- and 4-year expirations, following the procedure in Kitsul and Wright (2013). The three maturities correspond approximately to the expiration dates on the inflation options targeted by our predictive ML algorithm.

Table 5 shows the results from a structural break analysis of a linear relationship between inflation and rate uncertainty following the methodology of Bai and Perron (1998). For each column, the

Year	Topic	Percentage
2020	Economic growth and consumer behavior	26
	Government policy	15
	Energy and Commodity Prices	12
	Inflation and Price Dynamics	11
	Supply Chain Challenges and Disruptions	7
2021	Economic growth and consumer behavior	34
	Supply Chain Challenges and Disruptions	26
	Energy and Commodity Prices	13
	Inflation and Price Dynamics	11
	Financial Market Volatility and Investment Risks	10
2022	Energy and Commodity Prices	33
	Economic growth and consumer behavior	21
	Supply Chain Challenges and Disruptions	21
	Interest Rates and Monetary Policy	14
	Inflation and Price Dynamics	14
2023	Economic growth and consumer behavior	31
	Interest Rates and Monetary Policy	27
	Energy and Commodity Prices	20
	Inflation and Price Dynamics	17
	Financial Market Volatility and Investment Risks	14
2024	Economic growth and consumer behavior	34
	Inflation and Price Dynamics	23
	Interest Rates and Monetary Policy	21
	Energy and Commodity Prices	15
	Financial Market Volatility and Investment Risks	13

Table 4: Drivers of Inflation Uncertainty (2020-2024).

The table reports, for each year, the 5 topics with the highest relative importance in that year.

	2y	3y	5y
Break 1	2020m5	2020m6	2020m5
Break 2	2021m2	2021m3	2021m2
Break 3	2022m2	2022m2	2022m3
Wald Statistic	297.54	220.99	216.64
Number of Time Intervals	64	61	61
SSR	0.81	0.68	0.66
Trimming	0.15	0.15	0.15

The table reports structural break estimates for a linear regression model using the method of Bai and Perron (1998) with selection based on the Bayesian Information Criterion. The dependent variable is interest rate uncertainty (from Eurodollar options) for 2y, 3y and 4y maturities respectively and the independent variable is our market-based inflation uncertainty measure.

Table 5: Inflation vs Interest Rate Uncertainty.

dependent variable is interest rate uncertainty for that horizon and the independent variable is the corresponding measure of inflation uncertainty. The analysis rejects the null of no structural breaks and points to 3 breakpoints at 1% significance: first in early 2020 with the onset of the pandemic, followed by ones in early 2021 (as the recovery gathers steam) and 2022 (the start of the hiking cycle, the Russian invasion of Ukraine).

Break Period	Regression Coefficients			Average Relative Volatility		
	2y	3y	5y	2y	3y	5y
Start of sample - Break 1	-0.159**	0.104	-0.247	0.867	0.974	0.915
	(0.072)	(0.175)	(0.403)			
Break 1 - Break 2	0.043	-1.913	-0.428	0.517	0.522	0.489
	(0.662)	(1.136)	(0.418)			
Break 2 - Break 3	0.324	0.264	1.435***	0.986	0.981	0.889
	(0.256)	(0.381)	(0.408)			
Break 3 - End of Sample	0.435***	0.398**	0.405**	1.436	1.464	1.464
	(0.108)	(0.157)	(0.147)			

Standard errors in parentheses

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

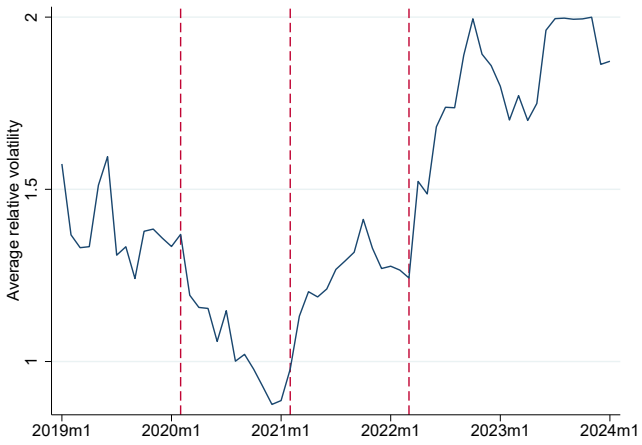
Table 6: Inflation vs Interest Rate Uncertainty.

The first 3 columns of Table 6 report the regression coefficients associated with the breaks estimated

in Table 5. Each row shows the coefficient for the time period from the end of one break to the next one. For example, Break 1 for the 2 year horizon corresponds to the sample period Jan 2019 (the start of our sample for this exercise) through Feb 2020, the first estimated break point. The table points to large swings, both in sign and magnitude, in the reduced form relationship between rate and inflation uncertainty, though the small numebr of observations makes estimates somewhat noisy.

The next 3 columns of the table show the average relative volatility (i.e. the average ratio of interest rate vol to inflation vol) for each of the periods identified by the break points. They show that interest rate vol declined relative to inflation vol during the early stages of the pandemic, but subsequently rebounded. Since 2023, in fact, the relative volatility has remained singificantly and persistently above pre-pandemic levels. This pattern can be seen clearly from Figure 13, which plots the ratio of interest rate volatility to our inflation uncertainty measure (both for the longest horizon). The estimated structural breaks for that horizon are also indicated in the figure. The graph shows that by the end of our sample (mid-2024), the relative vol is almost a third higher than 2019 levels. This is an interesting – and important – empirical pattern and merits further theoretical and empirical inquiry.

Figure 13: Interest Rate Uncertainty relative to Inflation Uncertainty, 2019-2024.



Note: This figure shows the ratio of interest rate uncertainty (over a 4y horizon) to our market-based inflation uncertainty measure (over a 5y horizon). The vertical lines mark structural break estimates reported in Table 5.

5 Conclusion

In this paper, we provided measures of inflation uncertainty for the United States, based on textual analysis of news articles performed using a Large Language Model as well as a machine-learning algorithm that employed a combination of market-based predictor variables. We compared our measures to other economic uncertainty measures as well as to survey data. As an application, we used the measures to

study the drivers of inflation uncertainty in the post-Covid era and to document structural shifts in the relationship of interest-rate uncertainty to inflation uncertainty.

While we focused on the United States, our approach can be used for constructing inflation uncertainty measures for several other countries (other than the United Kingdom) for which high-frequency inflation uncertainty measures are not available from inflation-linked options. On the macroeconomic side, it seems important to understand how consumer and firm behavior responds to inflation uncertainty as extant work has mostly focused on the level of inflation expectations or studied the effect of uncertainty in controlled settings rather than in real outcomes. On the policy front, it seems equally important to tease out the theoretical and empirical underpinnings of interest-rate uncertainty relative to inflation uncertainty, especially how expectations of central bank policy have evolved since the pandemic. In this sense, constructing a reliable inflation uncertainty index can have far-reaching applications, beyond just providing a key indicator of macroeconomic uncertainty.

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