Inflation Uncertainty: Measurement, Causes, and Consequences *

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Abstract

We measure and analyze inflation uncertainty in the US. We construct a novel composite indicator of inflation uncertainty (CIU) from two components: a news-based measure derived from textual analysis of newspaper articles using large language models and a market-based measure that draws on prices of options on exchange-traded funds and commodities. Unlike survey- or inflation-option-based measures, our index is available in real time and extends back to 1926. CIU reveals that inflation uncertainty spiked during the Great Depression, World War II, the 1970s and 1980s, following the Global Financial Crisis, and in the post-pandemic period. We highlight the driving forces behind these fluctuations in uncertainty and analyze their economic consequences. Heightened inflation uncertainty is associated with higher prices of real assets—such as gold, silver, and housing—but with lower prices of nominal assets, including government bonds, corporate bonds, and equities. Moreover, we find that increases in inflation uncertainty are followed by declines in private investment and real economic activity, irrespective of the underlying source of inflation uncertainty.

Keywords: Inflation uncertainty, inflation expectations, Large language models (LLM), financial options, commodity options.

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1 Introduction

Uncertainty about future inflation is widely viewed as economically costly. The literature has emphasized a number of channels—from firms and households delaying investment when nominal rates of return are more uncertain (Pindyck 1990) to investors shunning nominal assets such as bonds and stocks (e.g., Fischer and Modigliani 1978) to distorted resource allocation, reducing aggregate output (Woodford and Walsh 2005). Higher uncertainty is often cited as a key reason for why high inflation is harmful, based on the hypothesis that at higher rates, inflation becomes less predictable (Ball 1992). Additionally, high uncertainty may signal a de-anchoring of inflation expectations, undermining the central objective of monetary policy. Despite its importance for economists and policymakers, recent research in economics and finance has paid surprisingly little attention to inflation uncertainty, especially when compared to the earlier work which was often theoretical in nature (Okun 1971; Friedman 1977; Cukierman and Wachtel 1979; Cukierman and Meltzer 1986; Devereux 1989).

In part, this lack of attention may reflect the perceived stability of inflation in the pre-pandemic period; in part, it may be due to the lack of reliable measures available over an extended time series.[1] In this paper, we take up this challenge and provide a measure of inflation uncertainty that leverages a wide range of data and methodologies. Our composite indicator, the *Composite Inflation Uncertainty (CIU)*, is available in real time and extends back to 1926. Using CIU, we study the causes and consequences of inflation uncertainty. We find that higher inflation uncertainty imposes significant economic costs: it lowers the prices of risky nominal assets such as stocks and bonds, increasing the cost of capital for firms. This tightening of financial conditions is accompanied by a reduction in investment activity by both firms and households.

Our composite measure, the CIU, is defined as the first principal component of two measures constructed from two distinct sources. The first measure, which we call *Market-based Inflation Uncertainty (MIU)*, uses financial market data to capture the market's perceived uncertainty over future inflation. The most direct source of information about such perceptions are options on inflation (Kitsul and Wright 2013; Fleckenstein, Longstaff, and Lustig 2017). However, these were actively traded only for a short period (Mertens and Williams 2021). We, therefore, turn to traded options on bond exchange-traded funds (ETFs), from which we infer implied volatilities on nominal and real interest rates. With an assumption

[1] The following is an extract from a speech by John Williams, the President of the Federal Reserve Bank of New York (Williams 2022): "Assessment of the uncertainty criterion for well-anchored inflation expectations is more challenging given data limitations. In theory, prices on inflation options contracts could be used to infer investors' distributions of beliefs about future inflation. However, there have been virtually no trades recorded in the U.S. market for inflation caps and floors since 2015. Over that time, the "prices" reported for these options were based on models—not transaction prices—and cannot be used to measure investors' inflation uncertainty during the current episode."

on their correlation (we use the 3-month realized correlation between nominal and real rates as proxy), we can back out the implied volatility of inflation. The idea is that greater inflation uncertainty should manifest as higher nominal rate volatility relative to real rate volatility. The bond-ETF-option-implied inflation uncertainty is available starting in 2010. To extend the series back in time, we develop a predictive model that uses commodity price volatility as the primary input. When available, we use the implied volatility of options on commodity futures; when not, we use the realized volatility of commodity futures prices. Since commodity futures themselves are only available from 1959 (for gold and silver), we further extend the series back to 1926 by using realized volatility from broader commodity price indices and from gold- and energy-sector stock returns.

Our second measure, which we term *News-based Inflation Uncertainty (NIU)*, is based on a textual analysis of news articles using a Large Language Model (LLM).[2] Specifically, we use ChatGPT, one of the most widely known LLMs, to analyze the text of New York Times (NYT) articles related to business, the economy, and financial markets. For each article, ChatGPT is asked whether it directly relates to inflation uncertainty. If the answer is yes, ChatGPT is then prompted to assign a numerical score (from 1 to 100) reflecting the degree of uncertainty expressed in the article. Using these responses, we compute, for each month, two statistics: the share of articles flagged as related to inflation uncertainty and the mean intensity score across flagged articles. We then standardize both series and define NIU for a given month as the average of the standardized series. We rely on full-text articles available from 1980 onward and use lead paragraphs to extend the measure back to 1900.

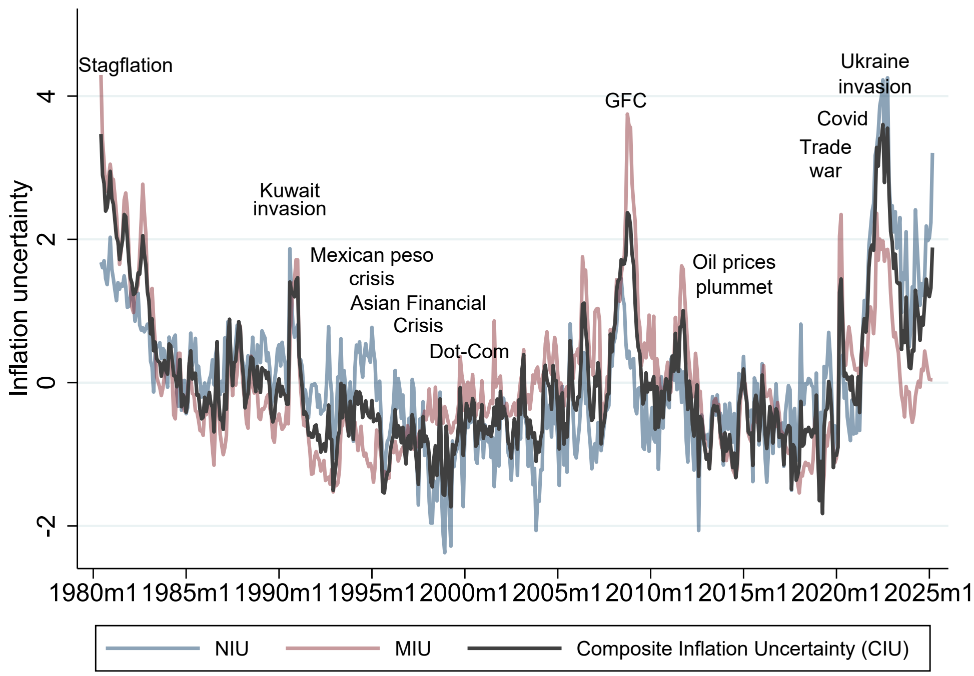
Figure 1 shows the time series of all three indices from 1980-2025 in Panel A, and from 1900-2025 onward in Panel B. The spikes in the series coincide with major historical events, including World War I, World War II, the Great Depression, the Kuwait invasion, the Mexican peso crisis, the Asian Financial Crisis, and the U.S.–China trade war. Three episodes stand out in particular: first, the stagflation of the early 1980s, during which market-based measures rose to unprecedented levels; second, the Global Financial Crisis (GFC); and third, the invasion of Ukraine, during which the news-based measures surged to previously unseen levels. Consistent with these patterns, we find that inflation uncertainty co-moves with policy, financial, and economic uncertainty, but also exhibits distinct variation.

In addition to verifying consistency with historical narratives, we also conduct an extensive validation of our inflation uncertainty measures. We conduct a human audit, comparing the mean intensity

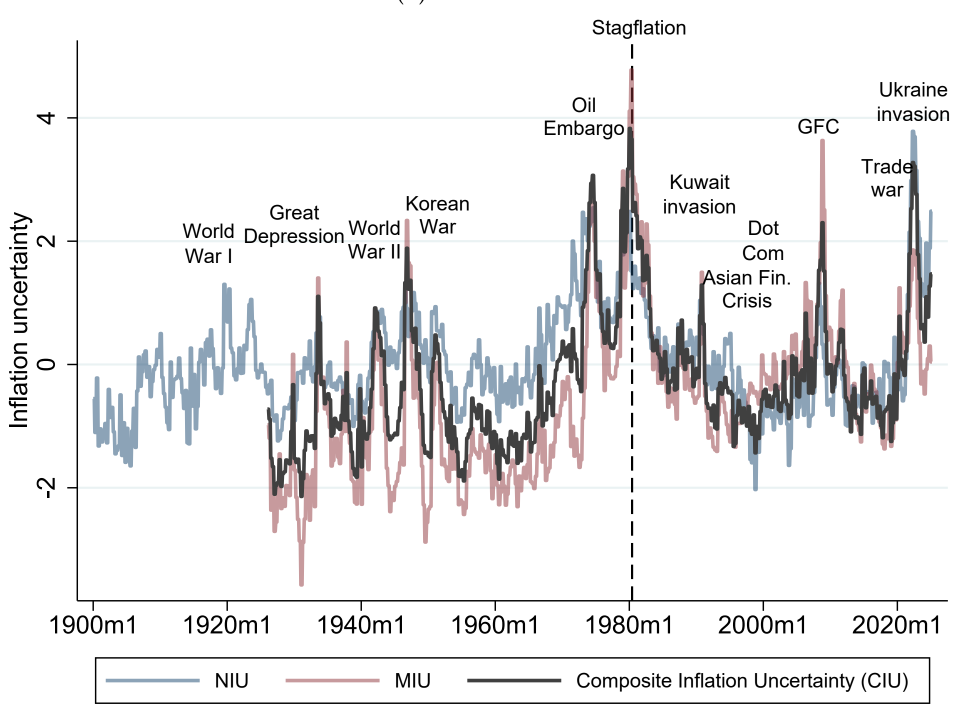
[2]LLMs are artificial intelligence models designed to understand and process human language using deep learning techniques, particularly neural networks. They are trained on vast corpora of text from diverse sources. Their ability to generate coherent responses and interpret context has made them increasingly influential across many domains. While their application in economics and finance is still in its early stages, recent work includes Bybee (2023); Castro and Leibovici (2024); Lopez-Lira and Tang (2023); Bauer, Huber, Offner, Renkel, and Wilms (2024); and Jha, Qian, Weber, and Yang (2024).

Figure 1: **Composite Inflation Uncertainty**

(A) 1980—2025



(B) 1900—2025



Note: This figure shows Composite Inflation Uncertainty (CIU), which is constructed as the first principal component of News-based Inflation Uncertainty (NIU) and Market-based Inflation Uncertainty (MIU). Panel A shows the main sample period starting in 1980. Panel B shows the full sample (including the historical extension) going back to 1926.

score assigned by the LLM with scores assigned by humans. We also compare our measure to alternative inflation uncertainty measures for sub-samples where these are available. First, MIU closely tracks implied inflation volatility computed from the prices of zero-coupon inflation caps and floors during 2010–2016 (e.g., Fleckenstein, Longstaff, and Lustig 2017), when those instruments were actively traded. Second, our news-based measure shows a strong correlation (between 66-83%) with survey-based indicators available starting in 2007. Third, higher levels of CIU are associated with larger forecast errors in consensus inflation forecasts. Finally, there is a strong positive relationship between CIU and disagreement among professional forecasters about the level of future inflation. Disagreement has often been used in the literature as a proxy for inflation uncertainty (e.g., Cukierman and Wachtel 1979; Wright 2011), despite a theoretically ambiguous link between the two objects.[3]

Next, we examine the effects of inflation uncertainty on macroeconomic aggregates and financial market variables, followed by an analysis of the forces driving fluctuations in uncertainty. A key advantage of our measure is the length of the time series, spanning periods of both high and low inflation, which allows for a more comprehensive analysis than previously possible.

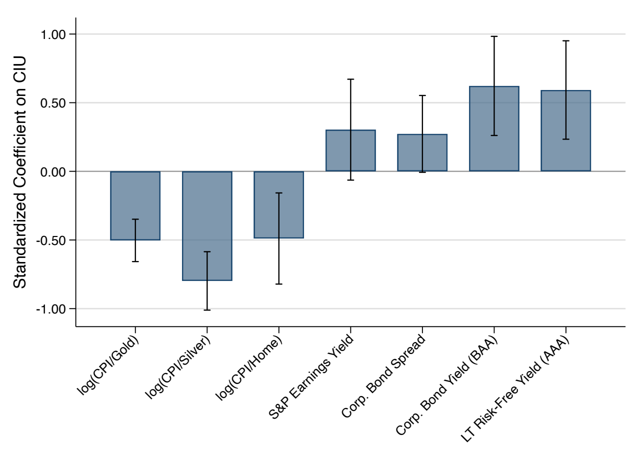
We begin by studying how asset prices respond to inflation uncertainty. One would expect real assets to become more desirable in the face of higher uncertainty about future price levels, as investors shift their portfolios toward real assets and away from nominal ones. The evidence supports this view: a one-standard-deviation increase in CIU is associated with a 0.5–0.8 standard-deviation rise in the log real prices of gold and silver and a 0.5 standard-deviation rise in log real home prices. In contrast, the long-term risk-free yield rises by about 0.6 standard deviations.

We then turn to the effects on business assets—more precisely, on claims (equity and debt) on such assets. The extent to which business assets are hedged against inflation risk is the subject of a long-standing debate in the literature. We find inflation uncertainty has a negative effect on both equity and debt claims. The S&P 500 (log) earnings yield rises by about 0.3 standard deviations, indicating substantial declines in equity valuations. Corporate bond yields rise by about 0.6 standard deviations and the BAA-AAA credit spread widens by about 0.3 standard deviations, implying that the cost of debt for firms rises more than risk-free rates. While this may partly reflect a debt-deflation channel (Kang and Pflueger 2015), we find that equity prices for non-levered firms also show a decline, suggesting the impact extends beyond balance sheet channels. Thus, our results lend support to the view that business assets behave more like nominal than real claims. In turn, they suggest firms face increased costs of capital as inflation uncertainty rises.

Next, we estimate the effects on macroeconomic aggregates, specifically investment and output.

[3]See Section 3.3.3.

Figure 2: **Relationship of Asset Prices with Inflation Uncertainty**



Note: This figure shows standardized coefficients from regressions of each asset's log inverse real price (gold, silver, housing) or yield (S&P earnings, corporate bonds, long-term risk-free) on inflation uncertainty (CIU) while controlling for the inflation level, the VIX, and the EPU over the 1926-2025 period; more details are provided in the notes of Table 7. A coefficient β means a 1-SD increase in CIU is associated with a β-SD change in the outcome. Whiskers are 90% confidence intervals based on Newey-West standard errors.

We use two approaches: a vector auto-regression (VAR) estimation and a local projection analysis using squared CPI announcement surprises as an instrument, defined as the difference between the actual CPI release and professional forecasters' expectations immediately prior to the announcement. We show a robust and persistent negative relationship with inflation uncertainty: periods of rising inflation uncertainty are followed by significant declines in investment and industrial production over the next few quarters. The estimated effects are economically meaningful: an increase of one standard deviation in the CIU over the past year predicts a decline in investment over the next three years of about 1-2 percentage points.

The significant effects of inflation uncertainty on financial markets and the real economy underscores the need to better understand what drives it. To date, the literature has largely focused on one channel: a higher *level* of inflation is associated with greater volatility and uncertainty, typically attributed to changing perceptions about monetary policy. In this view (Cukierman and Meltzer 1986; Ball 1992), private agents interpret high inflation as a signal that the central bank is less committed to maintaining price stability, thereby increasing uncertainty about future nominal prices. Our measure is uniquely suited to studying the level-uncertainty relationship, as it spans a wide range of inflation outcomes in the United States—both high and low. We find empirical support for the classic hypothesis: inflation uncertainty tends to be elevated during periods of high inflation.

However, we find evidence that other factors also play an important role in driving inflation uncertainty. First, inflation uncertainty tends to rise even at very low levels of inflation, suggesting a more nuanced relationship between level and uncertainty—what matters is not the level of inflation *per se*, but its deviation from a reference or target. Second, we find that CIU is positively related to the size of squared CPI announcement surprises. In other words, uncertainty increases when realized inflation deviates significantly from what market participants anticipated. This pattern is unlikely to reflect monetary policy learning, as it seems implausible that a CPI surprise reveals new information about the conduct of policy. Instead, it is more consistent with other forms of learning—for example, about shock volatilities or structural changes in the economy.

Our second exercise leverages the capabilities of large language models to deepen our understanding of the forces driving inflation uncertainty and to provide a more quantitative picture. We conduct a 'topic analysis' by asking ChatGPT to identify the key factor causing inflation uncertainty in each article flagged as being about inflation uncertainty. We then prompt the model to assign each identified factor to one of six categories: demand, supply, monetary policy, fiscal policy, trade policy, or financial factors. The share of articles assigned to each category serves as a proxy for the relative importance as a driver of inflation uncertainty. The results of the topic analysis point to supply-side factors—particularly those related to energy and commodity prices—as the most important drivers of inflation uncertainty, followed by monetary policy. Demand considerations rank third, while other factors, such as fiscal policy, trade policy, and financial factors, appear to be less salient over the entire sample. Having said that, the importance of these factors does change over time, for example, in recent years, trade policy has emerged as a key driver alongside supply factors and monetary policy.

A natural follow-up question is whether the macroeconomic consequences of inflation uncertainty depend on its underlying source. If the response varied sharply with the driver, that would point to source-specific, indirect mechanisms; if it were broadly invariant, it would suggest a more direct channel common to all firms — for example, a cost of capital channel. We find the latter: interacting our inflation uncertainty shock with the shares of articles attributing uncertainty to supply versus monetary policy (two main drivers identified above) does not yield differential effects on investment and industrial production. Combined with the asset-pricing evidence — rising equity yields and widening corporate bond spreads in the face of inflation uncertainty — this supports cost of capital as a primary channel through which inflation uncertainty depresses real activity.

This interpretation opens up a rich agenda for future work on cross-sectional heterogeneity in the cost-of-capital channel. Leverage likely amplifies a firm's exposure to inflation uncertainty, relative to all-equity financing, through the debt-deflation channel of Kang and Pflueger (2015); debt structure—short-term or floating versus long-term and fixed—plausibly shapes the response as well; and finally, firms whose cash flows co-move positively with inflation may provide a natural hedge that mutes valuation declines relative to firms with negative pass-through. Exploring these cross-sectional dimensions of the effect of inflation uncertainty is a natural direction for further work.

2 Related Literature

Our analysis contributes to a large and diverse body of work on the macroeconomic effects of uncertainty.[4] We focus on inflation uncertainty and make contributions on three fronts: measurement, effects, and drivers. We discuss each of these in more detail below.

Measurement of inflation uncertainty. Our first contribution is the development of new measures of inflation uncertainty. In this regard, the spirit of our exercise and inquiry is closer to the seminal contribution of Baker, Bloom, and Davis (2016) on economic policy uncertainty. Their news-based approach has been applied to measuring other forms of uncertainty, including monetary policy (Husted, Rogers, and Sun 2020), and geopolitical risk (Caldara and Iacoviello 2021). We build on this approach by exploiting recent advances in large language models (LLMs) for processing text, contributing to a growing body of research that brings LLMs into economics and finance.[5] Our strategy on using prices on financial options and assets to extract information about perceived inflation uncertainty is related to, e.g., Kitsul and Wright (2013), Fleckenstein, Longstaff, and Lustig (2017), Wright (2017), Mertens and Williams (2021), Hilscher, Raviv, and Reis (2022), and Bahaj, Czech, Ding, and Reis (2023). These works primarily use inflation derivatives, which were actively traded only for a short period of time in the US. We take a different approach—using options on bond ETFs and commodities—which allows us to construct a significantly longer time series. Our composite indicator, a combination of news and market-based information, offers a more direct alternative to other proxies for inflation uncertainty used in the literature—such as survey disagreement (Cukierman and Wachtel 1979), estimates from time-series models (Ball, Cecchetti, and Gordon 1990; Grier and Perry 1998; Londono, Ma, and Wilson 2024), estimates based on rounding in surveys (Binder 2017), probabilistic surveys (Armantier, Bruin, Potter, Topa, Van Der Klaauw, and Zafar 2013; Meyer and Sheng 2024) or quantile regressions (Lopez-Salido and Loria 2024).

[4]This literature is too voluminous to cite every worthy paper. A representative reading list will include Leahy and Whited (1996), Bloom (2009), Fernández-Villaverde, Guerrón-Quintana, Rubio-Ramirez, and Uribe (2011), Fernández-Villaverde, Guerrón-Quintana, Kuester, and Rubio-Ramírez (2015), Jurado, Ludvigson, and Ng (2015), Segal, Shaliastovich, and Yaron (2015), Brogaard and Detzel (2015), Baker, Bloom, and Davis (2016), Brogaard, Dai, Ngo, and Zhang (2020), Berger, Dew-Becker, and Giglio (2020), Ludvigson, Ma, and Ng (2021), Bekaert, Engstrom, and Xu (2022), and Baker, Bloom, and Terry (2024).

[5]See Bybee (2023), Lopez-Lira and Tang (2023), Jha, Qian, Weber, and Yang (2024), Kakhbod, Kogan, Li, and Papanikolaou (2024), and Acharya, Giglio, Pastore, Stroebel, Tan, and Yong (2025).

Effects of inflation uncertainty. Our contribution to the literature on implications of inflation uncertainty takes the form of new estimates for a broad set of financial and macroeconomic variables. On the asset pricing front, we provide a comprehensive treatment of a broad set of nominal and real assets, complementing early studies that have typically focused on a single asset class (Wright 2011; Kang and Pflueger 2015). On the macroeconomic front, a large body of theoretical work has emphasized the potential adverse consequences of heightened inflation uncertainty (Lucas 1973; Fischer and Modigliani 1978; Baldwin and Ruback 1986; Woodford and Walsh 2005). Empirical estimates are relatively sparse and often rely on inflation uncertainty measures backed out from time-series models (e.g., Huizinga 1993; Londono, Ma, and Wilson 2024). Working with a more direct measure of uncertainty and a long sample allows us to provide more robust estimates of the macroeconomic and financial consequences of inflation uncertainty. Our work complements recent studies analyzing the causal effect of inflation uncertainty using randomized control trials (RCTs) (Georgarakos, Gorodnichenko, Coibion, and Kenny 2024; Kostyshyna and Petersen 2024). [6]

Drivers of inflation uncertainty. Much of the existing literature on this topic is theoretical, highlighting the role of inflation levels and monetary policy in shaping inflation uncertainty. Ball (1992) argues that higher inflation makes the public less certain about the central bank's responsiveness, while Cukierman and Meltzer (1986) show that imperfect central bank credibility can generate a positive link between the level and uncertainty of inflation. Consistent with prior empirical work (Evans and Wachtel 1993), our analysis supports these mechanisms but also highlights the role of factors other than monetary policy in driving inflation uncertainty.

3 Measuring Inflation Uncertainty

In this section, we describe the construction of the *Composite Inflation Uncertainty* (CIU) index, which serves as our main measure of inflation uncertainty. CIU is a combination of two underlying measures: a *Market-based Inflation Uncertainty* (MIU) measure derived from option prices on bond ETFs and commodities, and a *News-based Inflation Uncertainty* (NIU) measure obtained from analyzing newspaper articles using a large language model (LLM). Below, we discuss the construction of each component in detail and validate them using external benchmarks. CIU is then defined as the first principal component of these two measures.

[6] Our analysis on the effects of inflation uncertainty is complementary to a large literature studying the effect of the level of inflation on asset returns – see, e.g., Fang, Liu, and Roussanov 2025, Pflueger 2025 and Cieslak, Li, and Pflueger 2024.

3.1 Market-Based Inflation Uncertainty (MIU)

For our market-based measure of inflation uncertainty, termed *Market-based Inflation Uncertainty* (MIU), we use prices of financial assets. The most directly relevant assets for this purpose are options on inflation. Unfortunately, in the United States, inflation caps and floors started trading only relatively recently (from about 2010) and have seen a significant erosion of liquidity/trading activity since about 2016 (Mertens and Williams 2021). We, therefore, pursue an alternative route: we extract the market's perceived inflation uncertainty from options on exchange-traded funds (ETFs), specifically those holding Treasurys and TIPS. Since nominal bond yields can be decomposed into real yields and inflation expectations, the difference between the implied volatilities of nominal and real yields contains information about the perceived inflation volatility (under the risk-neutral measure). Reliable market prices for these ETF options are available since 2010. To extend the measure backward in time, we use a predictive model: specifically, we exploit the tight relationship between the inflation uncertainty series extracted from ETF options and commodity price volatility to construct a predicted series of market-based inflation uncertainty.

3.1.1 Bond-ETF-Option-Implied Inflation Uncertainty

Although there are no exchange-traded funds (ETFs) investing in inflation-linked securities (such as inflation swaps), there are several that invest in nominal Treasury bonds and TIPS. We, therefore, obtain option data on TIPS and Treasury ETFs from OptionMetrics, available between May 2010 and March 2025.[7] For TIPS ETFs, we choose the ETF with the highest option trading volume, the *iShares TIPS Bond ETF* (ticker: TIP). It holds a portfolio with a maturity of at least one year and has an average duration of 7.7 years (see Appendix Figure A.1). From the set of Treasury ETFs, we pick the *iShares 7-10 Year Treasury Bond ETF* (ticker: IEF) since it has a similar duration and the related options are traded actively. We obtain implied volatilities for American calls and puts with a 3-month maturity (we use the average of the atm call and the atm put) struck at-the-money-forward (atm). OptionMetrics computes these implied volatilities by first using a Cox-Ross-Rubinstein binomial tree model to compute the implied volatility for each traded option and applying a kernel-smoothing technique to obtain a volatility surface across calls/puts, maturity, and strikes.

The implied volatilities from OptionMetrics are for the ETF price. We use the following approxima-

[7]The data contain information on American call and put options on the underlying ETFs, with option maturity ranging from 3-28 months. TIP options trade on the NYSE; IEF options trade on the NASDAQ. We obtain the duration of the bond ETFs from Bloomberg.

tion for the (log of the) two ETF prices at option expiry:

$$\ln P^{TIP}_{t+3m} \approx \ln P^{TIP}_t - Dur^{TIP} \cdot (r_{t+3m} - r_t) \tag{1}$$

$$\ln P^{IEF}_{t+3m} \approx \ln P^{IEF}_t - Dur^{IEF} \cdot (i_{t+3m} - i_t)\ , \tag{2}$$

where $Dur^j,\ j \in \{TIP, IEF\}$ denotes the (average) duration of the bonds underlying the ETF, while r_t and i_t denote the corresponding real and nominal rates, i.e. the (average) yield-to-maturity of the bonds underlying the ETFs.[8] The volatility of the ETF price can then be approximated by:

$$\sigma_t(\ln P^{TIP}_{t+3m}) \approx Dur^{TIP}\ \sigma_t(r_{t+3m}) \tag{3}$$

$$\sigma_t(\ln P^{IEF}_{t+3m}) \approx Dur^{IEF}\ \sigma_t(i_{t+3m})\ , \tag{4}$$

where $\sigma^2_t(x)$ denotes variance of x conditional on time-t information. Re-arranging, the implied volatilities for real and nominal rates can be recovered from the price volatilities:

$$\sigma_t(r_{t+3m}) \approx \frac{\sigma_t(\ln P^{TIP}_{t+3m})}{Dur^{TIP}} \qquad \sigma_t(i_{t+3m}) \approx \frac{\sigma_t(\ln P^{IEF}_{t+3m})}{Dur^{IEF}} \tag{5}$$

The Fisher identity implies

$$\pi^e_{t+3m} = i_{t+3m} - r_{t+3m}\ , \tag{6}$$

where π^e_{t+3m} denotes expected inflation (over a 10-year maturity) at time $t+3m$. This yields the following expression for the implied volatility of expected inflation, 3 months forward:

$$\sigma_t(\pi^e_{t+3m}) = \sqrt{\sigma^2_t(i_{t+3m}) + \sigma^2_t(r_{t+3m}) - 2 \cdot \rho_{t+3m} \cdot \sigma_t(i_{t+3m}) \cdot \sigma_t(r_{t+3m})} \tag{7}$$

where ρ_{t+3m} denotes the (risk-neutral) correlation between nominal rates i_{t+3m} and real rate r_{t+3m} from t through $t+3m$. This correlation is not directly observable. As our baseline, we proxy this with the realized correlation of the underlying ETF returns over a rolling 90-day window. We also consider a specification with a fixed correlation for the entire sample, where we use the unconditional average of the realized correlation of the underlying ETF returns over the full sample period. Appendix Figure A.2 compares the inflation uncertainty under both correlation assumptions; both measures are highly

[8]For TIPS, this approximation abstracts from the fact that cash-flows incorporate inflation with a small lag, about 3 months. Under some conditions (e.g. parallel shifts in inflation), this can be shown to induce a downward bias in the estimated inflation volatility. Quantitatively, however, the bias turns out to be very small (given the relatively long maturities of the underlying bonds): explicitly accounting for this feature involves adjusting our inflation volatility series by a factor of 1.03, see Appendix A.1.1.

correlated, with a correlation coefficient of 85%.

3.1.2 Prediction Model for Market-based Inflation Uncertainty

The bond-ETF-option-implied inflation uncertainty is available since mid-2010. To go back further in time, we use a predictive model relying primarily on the implied volatility of commodity options. Since commodity prices affect inflation, either directly by being included in the consumption basket such as for food, gasoline or heating costs, or indirectly by affecting the production costs of firms, one would expect a close relationship between the uncertainty about commodity prices and uncertainty about inflation.

We use commodity option data obtained from the Chicago Mercantile Exchange (CME) to construct a measure of implied volatility for commodity prices. In particular, we use option data on futures for gold (beginning 1982), silver (1984), corn (1985), soybean (1984), oil (1986), and natural gas (1984). We follow the CME's procedure to calculate the implied volatility of 3-month atm options on commodity futures; we provide a full description of the methodology in Appendix A.2.

When commodity options were not yet traded, and implied volatilities are unavailable for a commodity (e.g., in the early 1980s), we use the realized volatilities of 3-month futures as a proxy for implied volatility. We, therefore, obtain daily data on silver futures, gold futures, soybean futures and corn futures from Bloomberg. Since natural gas and oil futures only began trading a short time before the introduction of options, we instead rely on the realized volatility of stocks in the oil and gas industry. More concretely, we compute the realized volatility of stock prices for all firms in the "crude petroleum and gas" industry (SIC code 1311) and construct a weighted average across firms, using market capitalization as weights. With these realized volatility measures in hand, we construct proxies for implied volatility for periods in which only realized but not implied volatility is available. Specifically, we regress implied volatility on realized volatility over the overlapping sample and use the fitted values to extend the series into the non-overlapping period. Internet Appendix Figure A.3 plots the option-derived (black line) and the futures or stock price-derived volatility (light blue line). Both measures track each other closely. This is perhaps unsurprising since the futures contract we use to compute realized volatility is the underlying contract of the option. However, it nevertheless highlights that realized volatility is a good proxy for option-implied volatility.

Table A.1 provides summary statistics for the commodity price volatility in Panel A. It provides separate statistics for the period over which we have bond ETF option data (2010-2023) and our main sample period (1980-2025). The table shows that the rankings in terms of volatilities are fairly stable. Commodities that have a high volatility over the ETF sample period, such as natural gas, oil, and silver, also have a high volatility over the full sample. Commodities with lower volatilities, such as gold and corn, show a lower volatility in both samples. We then conduct a principal component analysis to extract the first three principal components of commodity price volatility. The first principal component (PC) loads fairly equally on all the individual components. The first PC explains 58.4% of the total variance, suggesting there is one dominant underlying factor. The second PC is a factor that loads strongly on the oil and gas volatility and loads negatively on corn and soybean. The first two components explain approximately 78.1% of total variance. The third factor loads slightly negatively on the volatility of gold and silver, and positively on the volatility of soybeans and corn. The first three PCs explain 88.2% of the total variance.

Equipped with our principal components of commodity volatility, we turn to our prediction model. The variable we predict is the bond-ETF-option-implied inflation uncertainty. The main predictive model is

$$\begin{aligned}\text{Inflation ivol}_t^{ETF} = \beta_0 + \beta_1 \cdot \text{Commodity ivol PC1}_t + \beta_2 \cdot \text{Commodity ivol PC2}_t \\ + \beta_3 \cdot \text{Commodity ivol PC3}_t + \beta_4 \cdot \text{CPI yoy}_t + \varepsilon_t,\end{aligned} \tag{8}$$

where Inflation ivol_t^{ETF} is the bond-ETF-option-implied inflation uncertainty, Commodity ivol PCj is the j-th principal component extracted from the commodity vol and CPI yoy_t is the year-over-year change in the consumer price index (FRED ticker: CPIAUCSL). We include the latter variable to capture a possible relationship between the first and the second moment of inflation. Summary statistics of the variables are provided in Panel B of Table A.1. The frequency of the data is monthly.

Table 1 shows the results of estimating our predictive model. It confirms the close relationship between inflation uncertainty and commodity price uncertainty. Column (1) shows that the first three principal components of commodity volatility explain 71% of the variation in inflation uncertainty. Column (2) documents that the level of inflation also helps predict inflation uncertainty. Together, commodity volatility and the level of inflation can explain 80% of the variation in the bond-ETF-implied inflation uncertainty. This suggests that our prediction model can reasonably be used to extend the time series of inflation uncertainty backward, beyond the period covered by the bond ETFs.

Columns (4) and (5) explore whether using data on inflation swaps improves the prediction model. We include the 5-year inflation swap rate (the level) as well as a 30-day realized volatility of the 5-year inflation swap. The results suggest that adding these variables only marginally increases the explanatory power. Column (6) tests how the predictive regression changes when we use a fixed correlation between real and nominal rates instead of a rolling-window correlation to compute bond-ETF-option-implied inflation uncertainty. Overall, we find that the set of variables that exhibit a statistically significant relationship with inflation uncertainty remains the same. However, the explanatory power decreases somewhat.

In Table A.2, we repeat the prediction exercise outlined in eq. (8) but focus on 3-month changes in the dependent variable Inflation ivol_t^{ETF}. We find that the coefficients are similar when predicting changes versus predicting levels. Column (3) shows that 3-month changes in the three principal components of commodity volatility and in the level of inflation capture around 60% of the variation of 3-month changes in inflation uncertainty. Column (6) shows that 3-month changes in the predicted value of eq. (8) explain the 3-month changes in the bond-ETF-option-implied inflation uncertainty with a coefficient that is close to one. The fact that our approach works almost equally well for changes versus level builds further confidence in our approach.

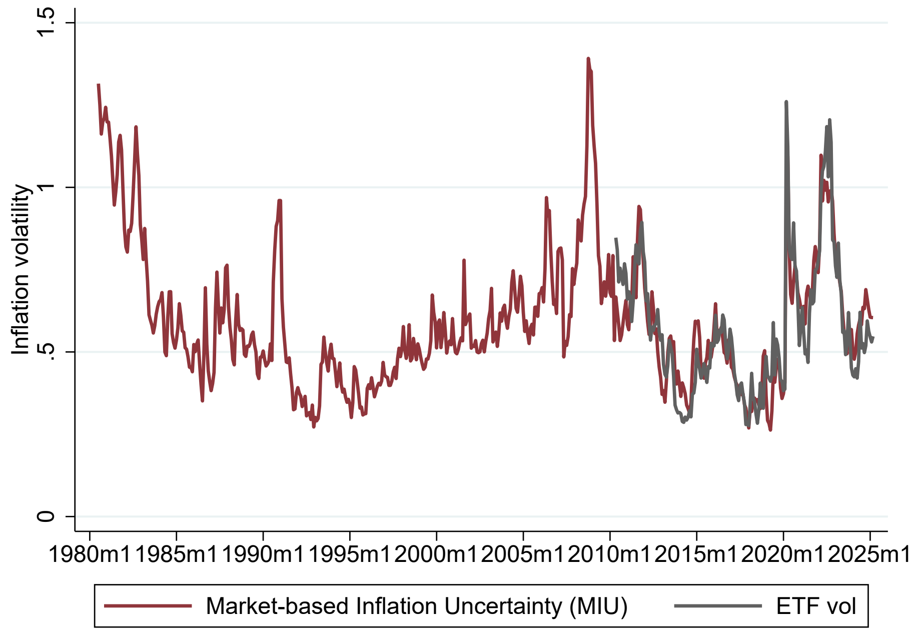
Based on the success of our prediction model, we construct *Market-based Inflation Uncertainty* (MIU) as the predicted values from the prediction model (8). Figure 3 plots the Market-based Inflation Uncertainty (MIU). MIU is high in the early 1980s, during the GFC, and in the post-pandemic period.

Table 1: Prediction Model for Market-based Inflation Uncertainty

	Inflation implied vol - ETFs					
	(1)	(2)	(3)	(4)	(5)	(6)
CME PC1	0.142***		0.129***	0.087***	0.095***	0.079***
	(0.014)		(0.011)	(0.012)	(0.009)	(0.013)
CME PC2	0.078***		0.055***	0.048***	0.032**	0.047***
	(0.014)		(0.011)	(0.014)	(0.014)	(0.018)
CME PC3	0.007		-0.030*	-0.012	-0.017	-0.004
	(0.018)		(0.017)	(0.014)	(0.014)	(0.015)
CPI yoy		0.110***	0.077***		0.087***	0.054***
		(0.030)	(0.016)		(0.023)	(0.017)
5y inflation swap (iswap)				0.027*	-0.034*	
				(0.015)	(0.019)	
30-day rvol 5y iswap				0.083***	0.053***	
				(0.014)	(0.014)	
Constant	0.630***	0.423***	0.521***	0.287***	0.541***	0.568***
	(0.021)	(0.060)	(0.035)	(0.074)	(0.079)	(0.030)
Observations	179	179	179	179	179	179
R^2	0.714	0.292	0.803	0.802	0.836	0.613
Correlation	Roll	Roll	Roll	Roll	Roll	Fixed

Note: This table shows the results of estimating the predictive model given in eq. (8). All x-variables have been standardized to a mean of zero and a standard deviation of one. The sample period is from May 2010 to March 2025. t-statistics based on Newey-West standard errors are shown in parentheses. Significance levels: *(p<0.10), **(p<0.05), ***(p<0.01).

Figure 3: **Market-based Inflation Uncertainty (MIU)**



Note: This figure shows the Market-based Inflation Uncertainty (MIU) and compares it with bond-ETF-option-implied inflation uncertainty, available from May 2010 to March 2025.

3.1.3 Validating MIU with Inflation Caps and Floors

Inflation options in the form of zero-coupon or year-on-year caps and floors started trading in the US after the Global Financial Crisis (GFC).[9] These derivatives are traded over the counter 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; Hilscher, Raviv, and Reis 2022). However, trading volumes have decreased markedly in recent years, making it increasingly difficult to obtain reliable transaction prices or quotes. This is why we relied on options on ETFs for our market-based measure.

Still, we can use the inflation options data for the period when they were actively traded (2010-2016) to validate our market-based measure. Specifically, we compare MIU to two inflation uncertainty measures derived from zero-coupon inflation caps and floors: first, the model-implied inflation spot volatility from Fleckenstein, Longstaff, and Lustig (2017)[10] and second, the 5-year option-implied inflation uncertainty. To construct the latter, we collect data on zero-coupon inflation caps and floors for the period 2010 to 2016 from Bloomberg. We then follow the methodology in Kitsul and Wright (2013) to

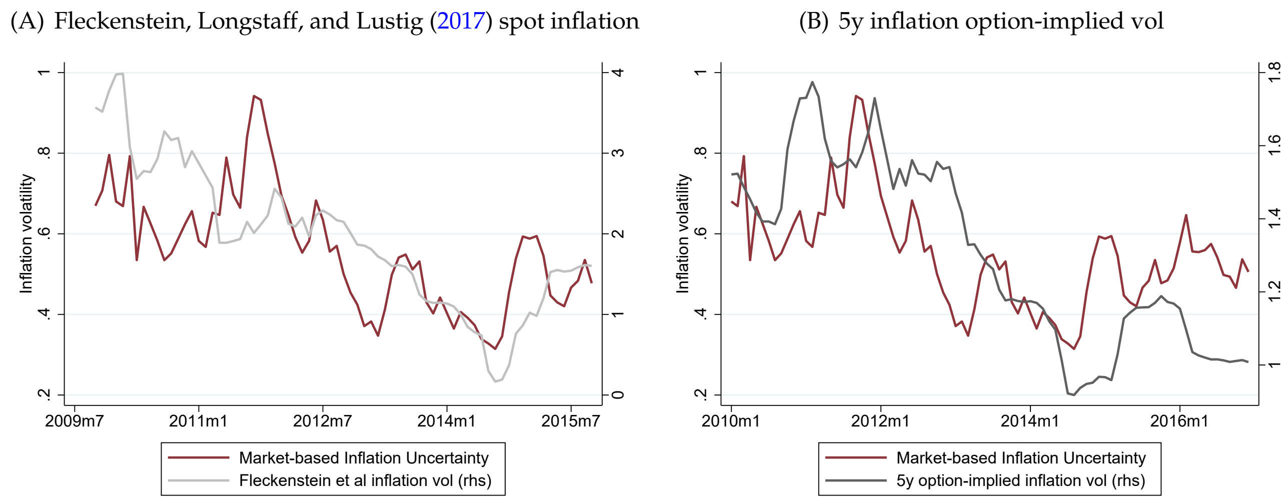
[9]The zero-coupon caps and floors have a single payoff at maturity, with the underlying being the realized inflation over the entire period, i.e. $payout = notional \cdot n \cdot (\text{realized inflation} - ((1 + strike)^n - 1))$.

[10]We thank the authors for sharing their data with us.

recover the implied inflation distribution.[11]

Figure 4 compares MIU to the inflation-option-uncertainty measures. Despite differences in maturity and the underlying inflation variable, the measures track each other reasonably well for the period in which they overlap, validating our approach to constructing a market-based measure.

Figure 4: **Validating MIU with Inflation-Option-Implied Inflation Uncertainty**



Note: This figure compares MIU to the model-implied inflation spot volatility from Fleckenstein, Longstaff, and Lustig (2017) in Panel (A) and inflation uncertainty implied by 5-year inflation caps and floors in Panel (B).

Table 2 conducts this validation more formally. We use the inflation uncertainty measures implied by inflation options as dependent variables in a predictive regression. For comparison, we also repeat the prediction eq. (8) with the bond-ETF-option-implied inflation uncertainty over the period over which the inflation options are available. All variables are standardized. We find a regression coefficient close to one when we use the predictive value from eq. (8) in columns (1), (3) and (5), with sizeable R-squareds. Thus, the prediction model seems to be valid also for other market-based measures of inflation uncertainty. Finally, we also use the full set of explanatory variables from eq. (8) in the predictive regression. Consistent with the results for bond-ETF-option-implied inflation uncertainty, we find that the 1st commodity vol PC is highly important across all dependent variables. Contrary to that, the importance of the inflation level varies.

[11]This involves constructing butterfly spreads for intermediate strikes and vertical spreads for outer strikes. The basic idea can be seen from the following example: 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.

Table 2: **Validating MIU with Inflation-Option-Implied Inflation Uncertainty**

	Spot vol		5y option		ETF vol	
	(1)	(2)	(3)	(4)	(5)	(6)
$\widehat{\text{Inflation ivol}}_t^{ETF}$	1.073***		1.161***		1.338***	
	(0.373)		(0.223)		(0.171)	
CME PC1		1.252**		0.896***		1.012***
		(0.489)		(0.334)		(0.218)
CME PC2		-0.037		-0.210		0.324***
		(0.296)		(0.142)		(0.067)
CME PC3		0.420**		0.172		0.115
		(0.208)		(0.214)		(0.143)
CPI yoy		-0.024		1.675**		1.437***
		(0.952)		(0.743)		(0.308)
Observations	66	66	79	79	79	79
R^2	0.307	0.488	0.304	0.544	0.660	0.709

Note: This table predicts inflation uncertainty implied by zero-coupon inflation caps and floors. The dependent variable is the model-implied inflation spot volatility from Fleckenstein, Longstaff, and Lustig (2017) in column (1) and (2), inflation uncertainty implied by 5-year inflation caps and floors in column (3) and (4), and ETF-implied volatility in column (5) and (6). The first measure is available between October 2009 and October 2015, the second between January 2010 and December 2016, and the third between May 2010 and March 2025. Significance levels: *(p<0.10), **(p<0.05), ***(p<0.01).

3.2 News-Based Inflation Uncertainty (NIU)

3.2.1 News Analysis

In this subsection, we describe the construction of *News-based Inflation Uncertainty* (NIU), constructed from news articles. Specifically, we use ChatGPT, a Large Language Model (LLM), to analyze the text of articles from the New York Times (NYT). We focus on NYT articles related to business, the economy and financial markets. Table 3 provides summary statistics about the set of articles used. Full-text articles, which are available between June 1980 and March 2025, contain on average more than five hundred words per article. By contrast, the first paragraphs of articles, which is available for a longer history going back to 1871 (though we only utilize the data from 1900 onward), contain around 24 words per article on average. We start by presenting results using full text articles (from 1980 to 2025) and then extend our measure back to 1900 using the lead paragraphs.

We use ChatGPT to analyze each NYT article by feeding in the prompt shown in Figure 5. First, we ask the LLM to assess whether an article makes a direct reference to inflation uncertainty (Q1). Second, for those articles related to inflation uncertainty per Q1, we ask ChatGPT to assign a numerical score (from 1-100) to each of these articles based on the degree of uncertainty about inflation expressed in it,

Table 3: Descriptive Statistics of NYT Articles

	Full text	Lead paragraph
Number of months	538	1,502
First month	June 1980	Jan 1900
Last month	March 2025	March 2025
Total number of articles in Business Financial	512,672	964,912
Total number of articles in Business	33,217	887,569
Total number of articles in Money, Business, Financial	27,519	20,992
Total number of articles	573,408	1,873,473
Average number of words per article	503.7	24.3

Note: This table shows the number of New York Times articles that are related to business news. There was a New York City newspaper strike from August 10th to November 5, 1978, causing there to be no articles for this period.

with 1 denoting a high degree of stability and 100 a high degree of uncertainty (Q2). Third, we ask the LLM about the key factor driving inflation uncertainty (Q3).

Figure 5: **ChatGPT Prompt**

Read the following news article: {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.

Q3: If your answer to Q1 is yes, what is the key factor causing inflation uncertainty according to the article?

Answer should be the factor described in one to two words.

Model version: ChatGPT 4o. Temperature: 0.0.

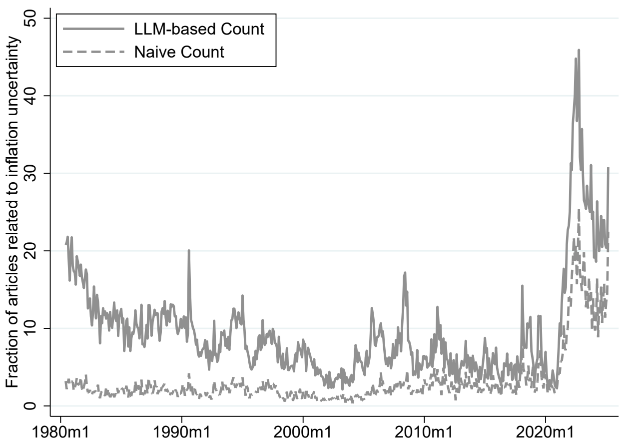
Panel A of Figure 6 reports the fraction of articles that the LLM identifies as being directly related to inflation uncertainty at a monthly level. On average, the LLM flags about 10% of articles as being related to inflation uncertainty. The time-series patterns are intuitive: uncertainty was high at the start of our sample—corresponding to the peak of the 1970s inflation surge—but declined more or less steadily for the next two decades. The post-pandemic period shows a huge surge: the number of articles related to inflation uncertainty rose to almost 45% in 2021 before stabilizing at just over 20%.

The figure also compares the LLM-based count to a more naive count approach that simply counts whether articles contain the words "inflation" and "uncertainty", similar to the approach of Baker, Bloom, and Davis (2016).[12] Compared to the naive count, the LLM flags a higher fraction of articles

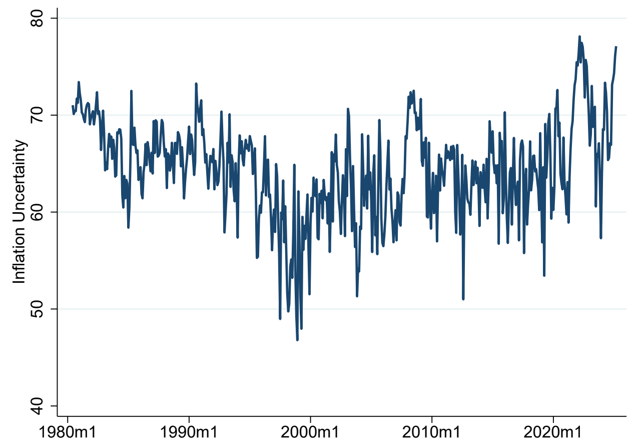
[12] We define an article as being related to inflation uncertainty when it contains at least one word from the list of words "inflation", "cpi", "pce", "consumer price" and at least one word from the list of words "uncertainty", "uncertain", "volatile", "volatility", "risk", "risky".

Figure 6: **News-Based Inflation Uncertainty**

(A) Fraction of articles related to inflation uncertainty (Q1)



(B) Average monthly intensity score (Q2)



Note: This figure shows inflation uncertainty identified from an analysis of New York Times articles using ChatGPT. The left panel shows the monthly fraction of business-related articles flagged by the LLM as pertaining directly to inflation uncertainty. This is compared with a "naive" count of articles which contain both the words "inflation" and "uncertainty". The right panel shows the average inflation uncertainty intensity score assigned by the LLM (on a scale from 1-100) to articles in a given month. News-based Inflation Uncertainty (NIU) is then the average of the standardized LLM count and the standardized LLM intensity score. The sample period is from June 1980 to March 2025.

as related to inflation uncertainty. This is perhaps expected, as the LLM can analyze the full context of each article. While the average levels are different, the broad time-series patterns of the LLM count and the naïve count are fairly similar (the time-series correlation is 85%). Appendix Figure B.4 reports several articles that the LLM classifies as related to inflation uncertainty but that are excluded by the naive count measure.

We then prompt ChatGPT to assign a numerical score (from 1 to 100) to the degree of the inflation uncertainty in each flagged article. These article-level intensity scores, which leverage the power of LLMs (relative to word counts, for example), are averaged to get a monthly intensity score.[13] Panel B of Figure 6 shows the time-series pattern of the intensity scores. The broad patterns are similar to the LLM count measure, uncertainty is high in the early 1980s, during the Global Financial Crisis (GFC), and in the post-pandemic period. Relative to the count-based series, these episodes look more similar to each other under the intensity measure.

We standardize the LLM count and intensity measures and then take their average to construct the *News-based Inflation Uncertainty* (NIU) series.

[13]The distribution of the intensity scores across all inflation-uncertainty-related articles is shown in Figure B.5.

3.2.2 Human Audit of Intensity Score

Prior research on the application of large language models emphasizes the importance of human validation of LLM-based scores for credibility, benchmarking, and error diagnosis (e.g., Dell 2025). To validate the LLM-based intensity scores, we therefore conduct a human audit on a subsample of articles. We select four months—two associated with high inflation uncertainty (April 1982 and February 2022) and two with low inflation uncertainty (March 1999 and May 2016)—and randomly sample up to 50 articles per month that were flagged by the LLM as related to inflation uncertainty, yielding a total of 155 articles. We develop detailed instructions to guide human auditors in rating these articles (see Appendix Figure B.6). The articles are presented in random order to five human auditors (three research associates not otherwise involved in the project and two authors), who independently rate each article on a five-point scale ranging from 1 (low uncertainty) to 5 (high uncertainty).

Appendix Figure B.7 compares the LLM-based inflation uncertainty intensity score with the average score assigned by human auditors. To make the scales comparable, we discretize the LLM-based intensity score into five quintiles. The figure shows a strong positive relationship between the LLM-based and human-assessed scores, with a correlation coefficient of 68%.

Table 4 provides further detail by reporting pairwise correlations between the intensity scores assigned by ChatGPT and those assigned by individual human auditors, as well as correlations among human auditors. The average correlation between two human auditors is 51%, underscoring that assessing inflation uncertainty based on article content is a non-trivial task. In particular, judgments often require mapping qualitative information into expectations about inflation risk, a process that may depend on the auditor's implicit macroeconomic framework.[14]

Consistent with this interpretation, ChatGPT's ratings exhibit an average correlation of 53% with individual human auditors, comparable to inter-auditor agreement. Thus, while ChatGPT does not outperform human judgment on an article-by-article basis, it performs comparably to an average human auditor while enabling classification at scale, including for more than half a million New York Times articles.

3.2.3 Validating NIU with Survey Data

In this subsection, we compare NIU to survey-based measures of inflation uncertainty (for the period in which the latter are available). These measures are constructed from surveys that ask respondents to assign probabilities to different inflation outcomes (usually in the form of ranges), thereby recovering the perceived distribution of inflation. While this approach places some demands on respondents, it

[14] Appendix Figure B.8 provides two example articles with the human and the LLM-based intensity assessment.

Table 4: Human Audit: Correlations of Intensity Scores

	(1)	(2)	(3)	(4)	(5)	(6)
(1) ChatGPT	1.00					
(2) Human 1 (RA)	0.62***	1.00				
(3) Human 2 (RA)	0.53***	0.52***	1.00			
(4) Human 3 (RA)	0.47***	0.52***	0.48***	1.00		
(5) Human 4 (Author)	0.53***	0.60***	0.38***	0.45***	1.00	
(6) Human 5 (Author)	0.51***	0.57***	0.50***	0.46***	0.60***	1.00

Note: This table reports pairwise correlations between the LLM-based inflation uncertainty intensity score and the intensity scores assigned by individual human auditors, as well as correlations among auditors. The sample consists of 155 articles included in the human audit. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

provides valuable information on the perceived uncertainty. We focus on the two main surveys that elicit the distributions of professional forecasters and households: the Survey of Professional Forecasters (SPF) and the Survey of Consumer Expectations (SCE). Since these surveys are now widely used in the literature, we discuss them only briefly in the main text and provide a more detailed explanation in Internet Appendix Section C.

Table 5 shows that NIU is a strong predictor of survey-based inflation uncertainty. For the SCE, a one standard deviation increase in NIU is associated with a 0.83 standard deviation increase in 1-year-ahead uncertainty (column 1), explaining over 68% of the variation in SCE-measured inflation uncertainty. This relationship remains strong for 3-year-ahead expectations, with a coefficient of 0.78 and an R^2 of 0.61 (column 3). Columns 2 and 4 analyze the predictive power of the individual components of NIU. Both the LLM-based count and the LLM intensity score are significantly related to survey-based inflation uncertainty. By contrast, the coefficient of the naive count is insignificant and even negative when controlling for the sub-components of NIU. This illustrates the power of using a large language model to analyze the news articles.

Results are similar for the SPF: NIU is strongly associated with professional forecasters' 1-year-ahead core CPI uncertainty (column 5). The coefficients of the LLM-based count and LLM-based intensity score are comparable to the SCE measure. The naive count is again negatively related to SPF-based uncertainty once the LLM-based measures are controlled for. Although the individual coefficients on the LLM measures are not statistically significant, a Wald test rejects the joint null that they are zero at the 1% level.

Figure 7 provides a visual comparison of NIU with survey-based measures from the SPF (Panel A) and SCE (Panel B). Across both panels, we observe that the survey-based uncertainty measures co-move with NIU, especially during key macroeconomic episodes. Both CIU and survey-based measures of in-

Table 5: **Validating NIU with Survey-based Uncertainty**

	SCE YoY				SPF Core YoY	
	(1)	(2)	(3)	(4)	(5)	(6)
	1y	1y	3y	3y	1y	1y
News-based Inflation Uncertainty (NIU)	0.826***		0.778***		0.658***	
	(0.061)		(0.068)		(0.130)	
LLM intensity		0.244***		0.194***		0.179
		(0.091)		(0.072)		(0.124)
LLM count		0.452***		0.495***		0.508
		(0.107)		(0.110)		(0.324)
Naive count		-0.059		-0.107		-0.115
		(0.117)		(0.112)		(0.359)
Observations	142	142	142	142	73	73
R^2	0.682	0.689	0.605	0.619	0.433	0.448
Joint test p-value (LLM = 0)		0.000		0.000		0.000

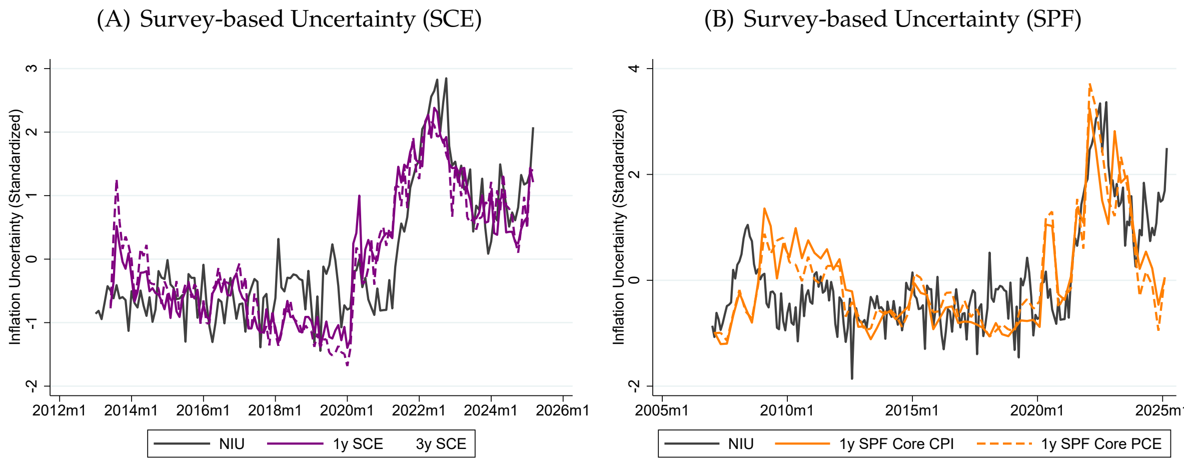
Note: This table compares NIU to survey-based inflation uncertainty obtained from probability forecasts in the SCE and SPF survey. SCE data is available on a monthly frequency between June 2013 and March 2025. SPF survey data is available on a quarterly frequency between 2007Q1 and 2025Q1. All variables are standardized. t-stats based on Newey-West standard errors are shown in parentheses. The table also reports the p-value from a Wald test of the joint null that the coefficients on LLM intensity and LLM count are zero, based on regressions that include the LLM measures but exclude the naive count benchmark. Significance levels: *(p<0.10), **(p<0.05), ***(p<0.01).

flation uncertainty are elevated following the Global Financial Crisis and gradually decline during the subsequent macroeconomic expansion. Both measures rose sharply at the onset of the COVID-19 pandemic and spiked again in 2022 amid the surge in realized inflation and heightened policy uncertainty. Taken together, the findings underscore the validity of NIU.

3.2.4 Testing for Look-ahead Bias

Using large language models offers several advantages—such as scalability, consistency, and the ability to capture context beyond keyword counts—but it also raises potential concerns. A key issue is whether LLMs introduce forward-looking bias, given that they are trained on text corpora up to a specific cut-off date. To address this, we exploit the information cut-off of GPT-3.5-turbo (September 2021) and re-estimate our measures. We then compare its outputs (unaffected by post-2021 information) with those from GPT-4o-mini, which may embed forward-looking bias, over the period after October 2021. As shown in Appendix Figure B.9, GPT-4o-mini classifies somewhat more articles as related to inflation uncertainty. Nevertheless, the time-series dynamics of both the count and intensity measures remain highly correlated across models, with correlation coefficients of 90% and 83%, respectively.

Figure 7: **Comparison with Survey-Based Inflation Uncertainty**



Note: This figure compares NIU to survey-based inflation uncertainty obtained from probability-forecasts in the SCE and SPF survey. SCE data is available on a monthly frequency between June 2013 and March 2025. SPF survey data is available on a quarterly frequency between 2007Q1 and 2025Q1.

3.3 Composite Inflation Uncertainty (CIU)

We have constructed two measures of inflation uncertainty; the NIU from news and the MIU from option prices. Both measures exhibit similar times-series dynamics as evidenced by a time-series correlation of 53%. To remove any idiosyncrasies of the individual measures, we construct the Composite Inflation Uncertainty (CIU) as the first principal component of MIU and NIU—explaining 77% of the variation in the subindices.

Panel A of Figure 1 shows the time series of the CIU. We find that many spikes are associated with important events, such as the Kuwait invasion, the Mexican peso crisis, the Asian Financial Crisis, or the US-China trade war. Two events stick out: firstly, the GFC, during which market-based inflation uncertainty rose to unprecedented levels, and secondly, the Ukraine invasion, during which news-based inflation uncertainty rose to unseen levels.

3.3.1 Extending the Sample

The measures described above span the period from 1980-2025, since the full text of the NYT articles is only available since 1980. In this subsection, we extend these measures back to 1900 for NIU and 1926 for MIU. We then construct a historical CIU as the first principal component of the historical NIU and MIU. Even though the underlying data sources become noisier and more sparse the further back we go, this approach allows us to generate a significantly longer time series, including episodes of large swings in inflation (in both directions). This in turn facilitates a more thorough analysis in the sections that follow.

Historical MIU. The historical extension of the MIU continues to leverage prediction model (8). In order to extend the commodity volatility back further, we need to use a larger array of data. As mentioned in earlier sections, we use the realized volatility from futures to allow for the construction of an imputed implied volatility metric to June 1980 (the earliest date of our main sample period). When extending our commodity data to 1926, however, we are limited by the availability of futures data. We, thus, use multiple other types of data. For metals (gold and silver), futures data are only available from April 1975. We extend the series back to 1951 using the three-month volatility of the BLS Metals Index, and prior to 1951 using the volatility of gold firms' stock returns (SIC 1041) from CRSP. For corn and soybeans, realized futures volatility is available from September 1959; between 1951 and 1959 we rely on the BLS Food Index, and before 1951 on the PPI Agriculture Index. In each case, we regress option-implied volatility on the substitute series and use the fitted slope to construct imputed volatility. For oil and natural gas, we continue to use the volatility of oil firms' stock returns (SIC 1311), which is available back to 1926 and thus provides the necessary historical extension. Appendix D provides further information.

Historical NIU. Prior to 1980, we use ChatGPT to analyze NYT lead paragraphs as described in Table 3, applying the same prompt shown in Figure 5 as for the full-text articles.[15] Although lead paragraphs are short (on average about 25 words), they provide a concise summary of the article's main content and thus a useful input for the LLM when assigning an inflation uncertainty intensity score. To assess comparability with the full-text measure, we test the correlation between the two series over the overlapping period (1980–2025) and find fairly high correlations (80% for the count and 50% for intensity). Both sub-components are standardized using the mean and standard deviation from the 1980-2025 period.[16]

Panel B of Figure 1 shows the evolution of CIU going back to 1926, together with the evolution of the NIU and MIU measures. From 1926 through the early 1930s, inflation uncertainty (CIU) remained relatively low but rose during the onset of the Great Depression, likely reflecting uncertainty about deflation and the collapse of financial institutions. Inflation uncertainty then declined through the mid-1930s, reaching a low point by the end of the decade. A sharp spike occurred in the early 1940s, peaking around 1942, likely due to wartime price controls, fiscal expansion, and uncertainty around monetary policy during World War II. After falling again in the mid-1940s, CIU rose sharply between 1946 and

[15] When the "lead paragraph" field is unavailable, we use the "snippet" field, and if that is also unavailable, the "abstract" field.

[16] Furthermore, we use a one-year transition period from June 1980 to June 1981 to transition from using purely the lead paragraph data to using the full-text data. During this period, we linearly decrease the weight on lead-paragraph data while correspondingly increasing the weight on full-text data. Thus, periods up to and including May 1980 receive a 100% weight on lead-paragraph data and 0% on full-text data, while periods from June 1981 onward receive a 0% weight on lead-paragraph data and 100% on full-text data.

1948, coinciding with the postwar removal of price controls and a surge in inflation. The 1950s and early 1960s marked a period of low inflation uncertainty. Starting in the late 1960s, however, CIU began to climb, with pronounced spikes in the mid-1970s and again around 1980. These increases coincide with the breakdown of Bretton Woods, oil price shocks, and growing doubts about the Federal Reserve's commitment to controlling inflation.

3.3.2 Does CIU Predict Forecast Errors?

When inflation uncertainty is high, agents are more uncertain about future inflation. In a rational view of the world, higher inflation uncertainty should, therefore, be associated with larger forecast errors. The (absolute) size of forecast errors can, therefore, be viewed as an alternative proxy for inflation uncertainty. We use consensus inflation forecasts from three different sources to test this: the Blue Chip Economic Indicators, the University of Michigan Survey of Consumers, and the Federal Reserve Greenbook (now Tealbook). We then estimate the following regression

$$|\mathbb{E}_t \Delta CPI_{t+h} - \Delta CPI_{t+h}| = \beta_0 + \beta_1 \mathrm{CIU}_t + \varepsilon_t \tag{9}$$

where $|\mathbb{E}_t \Delta CPI_{t+h} - \Delta CPI_{t+h}|$ is the absolute forecast error for the year-over-year change in CPI h-quarters ahead and CIU_t is the CIU index at time t. For example, with the Blue Chip survey and $h = 1$, we compare the forecast of year-over-year inflation one quarter ahead—of which three of the four quarters are already observed—with the realized value.

Panel A of Table 6 finds that higher inflation uncertainty is associated with larger ex-post forecast errors, both for unsophisticated agents such as households and for sophisticated forecasters such as professionals and Fed staff. For Blue Chip forecasts, a one standard deviation increase in CIU is associated with a 0.52 standard deviation rise in the absolute error for one-quarter-ahead forecasts, and a 0.31 standard deviation increase for one-year-ahead forecasts. In the Michigan survey, a one standard deviation increase in CIU is linked to a 0.29 standard deviation increase in households' year-ahead forecast errors.

Appendix Figure E.10 compares the time series of CIU and survey forecast errors, revealing a close relationship over multiple decades. Forecast errors were particularly large during the 1980s, the Global Financial Crisis, and the post-pandemic period—exactly when inflation uncertainty was elevated. Notably, the figure suggests that forecast errors and inflation uncertainty do not always move in lockstep: inflation uncertainty often rises after forecast errors materialize. For example, in the early post-pandemic period, inflation uncertainty and inflation forecasts remained low. As realized inflation began to exceed expectations, inflation uncertainty increased accordingly.

Table 6: **Comparison with Inflation Forecast Errors and Disagreement**

Panel A: Survey forecast errors (absolute amount)

	Blue Chip YoY		Michigan YoY	Greenbook QoQ	
	(1)	(2)	(3)	(4)	(5)
	h=1Q	4Q	4Q	1Q	4Q
Composite Inflation Uncertainty (CIU)	0.524***	0.311**	0.293**	0.471***	0.201**
	(2.85)	(1.98)	(2.40)	(6.04)	(2.52)
Observations	461	461	566	324	324
R^2	0.209	0.073	0.108	0.224	0.041

Panel B: Inflation disagreement

	Blue Chip YoY		Michigan YoY	FOMC SEP YoY		
	(1)	(2)	(3)	(4)	(5)	(6)
	h=1Q	4Q	4Q	YE	1y YE	2y YE
Composite Inflation Uncertainty (CIU)	0.755***	0.700***	0.645***	0.512***	0.493***	0.267***
	(7.38)	(8.99)	(9.20)	(6.43)	(5.39)	(2.72)
Observations	461	461	567	66	66	66
R^2	0.436	0.375	0.520	0.339	0.314	0.092

Note: This table relates CIU to inflation forecast errors and disagreement. Panel A predicts (standardized) absolute inflation forecast errors with inflation uncertainty following eq. (9), where h denotes the forecast horizon. The Blue Chip and Michigan are year-over-year forecasts, while the Greenbook forecasts are quarter-over-quarter forecasts. The Blue Chip forecasts are available on a monthly basis from December 1984 to April 2023, the Michigan forecasts are available monthly from January 1978 to March 2025, the Greenbook is available for each FOMC meeting from October 1979 to November 2019. Panel B relates inflation uncertainty to inflation disagreement as measured by the dispersion in surveys. $h = 1$ ($h = 4$) denotes the forecast one quarter (one year) ahead for year-over-year inflation, while "YE" refers to forecasts for the end of the current year, with "1y YE" and "2y YE" indicating forecasts for the end of the next year and the year after, respectively. The FOMC inflation forecasts are available for every other FOMC meeting between October 2007 and March 2025 (January 2012 and March 2025). All variables are standardized. t-stats based on Newey-West standard errors are shown in parentheses. Significance levels: *(p<0.10), **(p<0.05), ***(p<0.01).

3.3.3 Relationship with Inflation Disagreement

Previous studies have often relied on inflation disagreement as a proxy for uncertainty (Cukierman and Wachtel 1979; Wright 2011), albeit this is not without controversy (Rich and Tracy 2010).[17] Interestingly, since measures of disagreement have been readily available for some time, inflation disagreement has been more thoroughly studied than inflation uncertainty (e.g., Mankiw, Reis, and Wolfers 2003). In this subsection, we show that our inflation uncertainty index and various measures of inflation forecast disagreement exhibit a strong correspondence. To the extent that both measures are subject to noise/measurement error, this finding provides a degree of validation.

[17] Theoretically, the relationship is ambiguous. For example, in a simple linear Gaussian setting, there is a non-monotonic relationship between uncertainty and dispersion: a decrease in the precision of signals increases uncertainty but could increase or decrease dispersion, as illustrated in Appendix F.

To measure disagreement, we use data from three sources: the University of Michigan Survey, the Blue Chip survey and the Fed's Summary of Economic Projections (SEP). For the first two surveys, we use the standard deviation across all forecasters' forecasts for year-over-year inflation as a measure of disagreement. Since individual forecasts are only available with a five-year lag for the SEP, we use the range (highest minus the lowest forecast) for PCE inflation. The FOMC provides forecasts for the level of year-over-year inflation at the end of the current year ("YE"), at the end of the next year ("1y YE") as well as for the following year ("2y YE").

Table 6 shows that CIU is strongly and positively associated with disagreement across all measures: a one standard deviation increase in CIU corresponds to roughly a 0.5 standard deviation rise in disagreement about future inflation. This result holds consistently across different types of forecasters—including households, professional forecasters, and FOMC participants. Appendix Figure F.12 confirms the close relationship between inflation uncertainty and disagreement in the time series.

3.3.4 Comparison with Other Uncertainty Measures

Next, we compare inflation uncertainty with other forms of uncertainty, including policy, interest rate, equity market, and real economic uncertainty. We compute correlations of CIU with Economic Policy Uncertainty (EPU), Monetary Policy Uncertainty (MPU) (Husted, Rogers, and Sun 2020), the MOVE index, the VIX index, and 3-month real economic uncertainty (JLN) (Jurado, Ludvigson, and Ng 2015; Ludvigson, Ma, and Ng 2021). CIU is positively correlated with all five measures, with correlation coefficients of 0.30 (EPU), 0.31 (MPU), 0.40 (MOVE), 0.39 (VIX), and 0.44 (JLN). The joint R^2 from predicting CIU with the entire set of uncertainty proxies is 0.46. These results indicate that inflation uncertainty shares common elements with other uncertainties, yet also features distinct variation not explained by broader economic or policy uncertainty.

4 Effects of Inflation Uncertainty

In this section, we study the macro and financial consequences of inflation uncertainty.

4.1 Asset Prices

One potential channel through which inflation uncertainty may affect the real economy is via its impact on asset prices—particularly through shifts in the relative pricing of nominal versus real assets. As Fischer and Modigliani (1978) put it, *"increased uncertainty about future prices reduces the safety of nom-*

inal assets, and increases the relative attractiveness of real assets as inflation hedges".[18] Yet the question of how inflation uncertainty shapes the pricing of nominal versus real assets in the data remains largely unexplored.

To examine this formally, we estimate the monthly regression

$$\text{Price}_t = \beta_0 + \beta_1 \cdot \text{CIU}_t + \beta_2 \text{CPI yoy}_t + \beta_3 \cdot \text{Uncertainty Controls}_t + \epsilon_t. \tag{10}$$

This regression therefore relates the price of an asset in month t to the inflation uncertainty in month t, controlling for the level of inflation and various other uncertainty measures. Table 7 shows the relationship of CIU with various asset prices over the 1926-2025 period. Panel (A) contrasts nominal and real assets with estimates for gold, silver, housing and nominal long-term bonds. For gold and silver, we use the nominal spot price indices, obtained from Finaeon, and scale them by the CPI index. For housing, we use the real home price index from Robert Shiller's website.[19] For long-term bonds, the dependent variable is the yield on Moody's AAA-rated corporate bonds. Columns (1)-(6) show that higher inflation uncertainty makes real assets (gold, silver and housing) more attractive to investors: a 1-standard deviation increase in inflation uncertainty raises the real price of gold and silver by 26-37% and that of housing by about 9-12%. In contrast, nominal bond yields rise by about 1.1-1.4 percentage points, implying a price decline of roughly 11-14% for a bond with a 10-year duration (columns 7-8). These patterns are robust to including controls for the level of inflation as well as other measures of uncertainty.

The extent to which stocks—or more broadly, claims on business assets—are a hedge against inflation risk has long been the subject of debate in the literature.[20] We leverage the length of our sample to document new facts about how market prices of these assets respond to fluctuations in inflation risk. Panel (B) of Table 7 presents the estimated effect of CIU on equities and corporate bonds. The dependent variable in columns (1)-(3) is the log of the equity yield, defined as the ratio of the three-year average

[18] They go on to note: *"Residential structures occupy a prominent position among such assets, especially when the performance of the equity values is as disappointing as it has been in the recent inflation allover the world. Other assets the public may turn to include non-reproducible tangible wealth such as land, gold, art work, etc. Given the fixity of the supply, the prices of such assets will tend to be bid up faster than the general price level. It is entirely conceivable that the resulting "capital gains" increase in real wealth will result in a decline in saving and, finally, in physical investment."*

[19] Shiller constructs the home price index using four different sources. The nominal home price index for 1890–1934 is from Grebler, Blank, and Winnick (1956), based on homeowner surveys across 22 U.S. cities reporting both 1934 values and earlier purchase prices. For 1934–1953, Shiller constructed a median price index from newspaper advertisements in five cities (Chicago, Los Angeles, New Orleans, New York, and Washington, D.C.). The 1953–1975 index uses the home purchase component of the CPI, which tracked prices for homes of constant age and size. For 1975 to the present, the data come from the S&P/Case-Shiller U.S. National Home Price Index.

[20] See, for example, Fama and Schwert (1977), Chen, Roll, and Ross (1986), Katz, Lustig, and Nielsen (2017) and Fang, Liu, and Roussanov (2025).

Table 7: **Inflation Uncertainty and Asset Prices, 1926-2025**

(A) Nominal vs. real assets

	log(1/Real Gold Price)		log(1/Real Silver Price)		log(1/Real House Prices)		Long-term risk-free rate	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Composite Inflation Uncertainty (CIU)	-0.347***	-0.259***	-0.288***	-0.370***	-0.0945*	-0.124**	1.070**	1.444***
	(-5.32)	(-5.36)	(-4.81)	(-6.17)	(-1.77)	(-2.42)	(2.41)	(2.72)
Observations	1189	1189	1189	1189	1189	1189	1189	1189
R^2	0.280	0.542	0.365	0.473	0.106	0.260	0.209	0.252
CPI YoY	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Uncertainty Controls		Yes		Yes		Yes		Yes
Sample Start	1926m3	1926m3	1926m3	1926m3	1926m3	1926m3	1926m3	1926m3
Sample End	2025m3	2025m3	2025m3	2025m3	2025m3	2025m3	2025m3	2025m3

(B) Claims on business assets

	log(Earnings/Stock prices)			Corporate bond spread		Corporate bond yield	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Composite Inflation Uncertainty (CIU)	0.0673	0.0904	0.0801	0.392***	0.163	1.463***	1.606***
	(1.09)	(1.36)	(0.66)	(3.51)	(1.60)	(2.97)	(2.84)
Observations	1186	1186	540	1189	1189	1189	1189
R^2	0.060	0.126	0.274	0.303	0.480	0.219	0.251
CPI YoY	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Uncertainty Controls		Yes	Yes		Yes		Yes
Sample Start	1926m3	1926m3	1980m1	1926m3	1926m3	1926m3	1926m3
Sample End	2024m12	2024m12	2024m12	2025m3	2025m3	2025m3	2025m3

Note: This table shows regressions of asset price valuations on inflation uncertainty. The dependent variables in Panel (A) are: (i) the spot gold price obtained from Finaeon (formerly GlobalFinancialData) scaled by the CPI index, (ii) the spot silver price obtained from Finaeon scaled by the CPI index, (iii) the real home price index from Robert Shiller's website (this is only available on an annual frequency prior to 1952), (iv) the yield on Moody's AAA-rated corporate bonds (in %). The dependent variables in Panel (B) are: (i) the S&P 500 index to earnings where earnings are the three-year average of annual S&P 500 earnings before special items following Hillenbrand and McCarthy (2024), (ii) the yield difference between Moody's BAA-rated and AAA-rated corporate bonds (in %), (iii) the yield on Moody's BAA-rated corporate bonds (in %). All-equity financed firms are firms whose average quasi-market leverage is below 10% (leverage is computed as the ratio of long-term book debt to market equity plus long-term book debt). All regressions control for the level of inflation (CPI YoY). Controls for uncertainty are the EPU and the VIX. When VIX is not available, we impute the VIX with past 3-month realized volatility of stock market returns. t-stats based on Newey-West standard errors are reported in parentheses. The sample period is from March 1926 to March 2025. The equity yields are only available until December 2024. Significance levels: *(p<0.10), **(p<0.05), ***(p<0.01).

of annual S&P 500 earnings before special items to the level of the S&P 500 index. We use the "Street earnings" yield, based on earnings before special items (see Hillenbrand and McCarthy (2024)), which strips out transitory components and better captures the persistent, i.e., forward-looking, component of earnings.[21] For bonds, we use the yield on Moody's BAA-rated corporate bonds. Columns (4)-(5) show results for the spread relative to the AAA yield used in Panel (A). This spread, following Kang and Pflueger (2015), can be interpreted as a credit risk premium faced by firms. Columns (6)-(7) present the effect on the BAA yield.

The results are consistent with investors viewing business assets as more nominal than real, i.e.

[21]This means that—when price-earnings ratios are constructed to be robust to fluctuations in cash flow volatility and trend earnings growth—fluctuations in earnings yields can be interpreted as fluctuations in expected stock returns (Hillenbrand and McCarthy 2025). For these reasons, we do not use the CAPE ratio or scale stock prices by GAAP earnings.

poor hedges for inflation risk. Required rates of return for both equities and corporate bonds rise (or equivalently, valuations fall) with CIU. Equity prices fall by around 6-9%, leading to an increase in equity yields in response to a one–standard-deviation uptick in inflation uncertainty (controlling for the level of inflation and other forms of uncertainty). Interestingly, column (3) reveals that the estimated effect for all-equity firms is similar. While these coefficients are estimated with noise and statistically insignificant, the point estimates suggest that the negative effect of inflation uncertainty on stock valuations is likely not driven by leverage or the revaluation of nominal debt obligations. Columns (4)-(5) show that the corporate bond spread goes up by 16-39 bps in response to a one standard deviation increase in CIU. In other words, the cost of nominal corporate debt rises more than long-term risk-free rates.

This finding—higher uncertainty is associated with a higher risk premia on corporate assets—is also consistent with the higher-frequency evidence in Knox, Londono, Samadi, and Vissing-Jorgensen (2024). They find inflation announcement days are associated with significantly higher implied stock market volatility in the post-Covid sample, which they interpret as indicating a higher equity premium on those days. Our findings are also in line with Kang and Pflueger (2015), who show that greater inflation risk raises corporate bond spreads by increasing firms' exposure to debt deflation, where unexpectedly low inflation amplifies real debt burdens and default risk. Finally, Wright (2011) finds evidence that higher inflation uncertainty is associated with higher term premia on long-term bonds.

Together, these results show that uncertainty about the future value of nominal claims significantly raises the value of real assets, but also significantly drives up the cost of capital, especially for firms.

4.2 Investment and Economic Output

Next, we analyze the macroeconomic effects of inflation uncertainty, specifically on aggregate investment and output. Our results on firms' cost of capital indicate that higher inflation uncertainty is related to higher funding costs for firms. One might expect that higher costs for capital inputs would lead firms to cut back on investment. But there might also be other channels by which inflation uncertainty could impact investment. For example, higher inflation uncertainty makes it harder for firms to forecast revenues and costs, complicating long-term planning, budgeting, and contract writing. In addition, option theory suggests that there is value in waiting for more information about future prices, suggesting that firms delay or scale back investment, especially in irreversible projects.

We employ two econometric frameworks—vector auto-regressions (VAR) and local projections (LP)—to investigate this. The outcome variables of interest are investment and output. For the former, we use "Real Gross Private Domestic Investment" from the Bureau of Economic Analysis.[22] This series mea-

[22]Data are downloaded from FRED (ticker: GPDIC1).

sures the inflation-adjusted value of private-sector spending on fixed assets (both commercial and residential) and changes in private inventories within the United States. Since investment data are only available at a quarterly frequency, the analysis below proceeds on the quarterly level (we use the quarterly averages of variables available monthly). For output, we use the index of industrial production published by the Federal Reserve (FRED ticker: "INDPRO"), which measures the real value added by manufacturing, mining, and electric & gas utilities industries.

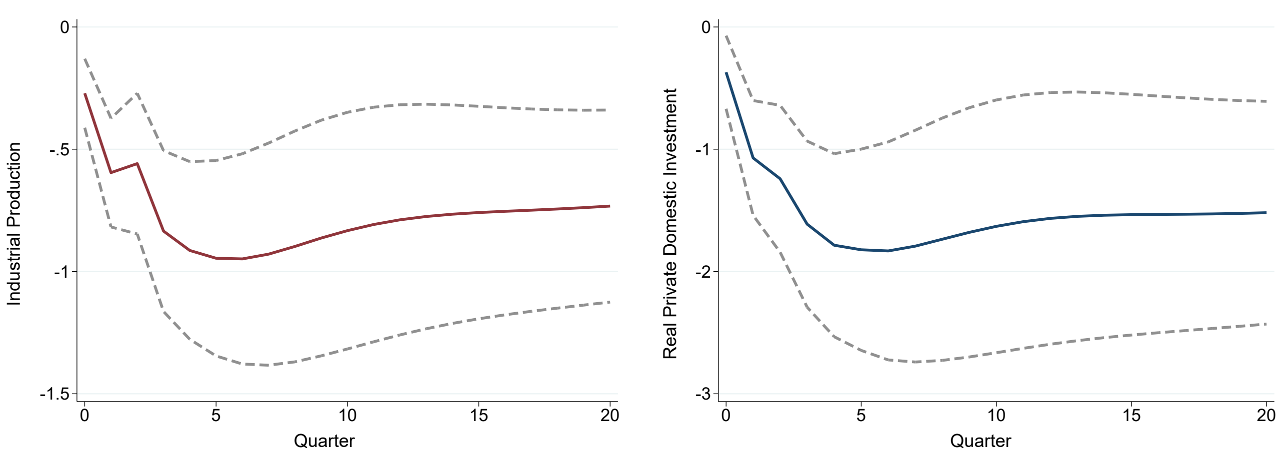
VAR analysis

We follow the approach in Baker, Bloom, and Davis (2016) and estimate a vector auto-regression (VAR) with our inflation uncertainty series added to the following set of macro variables: investment, industrial production, employment, and the S&P 500 index (all in logs) as well as the federal funds rate. To recover orthogonal shocks, we use a Cholesky decomposition with inflation uncertainty ordered first. This is equivalent to assuming that the other variables have no contemporaneous effect on inflation uncertainty. We include three lags of all variables.

Figure 8: **VAR: Response of investment & production to inflation uncertainty shock**

(A) Industrial production response to CIU shock

(B) Investment response to CIU shock



Note: This figure shows the impulse responses of industrial production (Panel A) and investment (Panel B) to inflation uncertainty shocks. The VAR is estimated using quarterly data from 1980Q3 to 2025Q1 with three lags. Identification is achieved via a Cholesky decomposition, ordering inflation uncertainty first. The gray lines show 90 percent confidence bands.

Figure 8 shows the estimated impulses. They depict the effect of a 1 standard deviation innovation to inflation uncertainty.[23] We find that a one standard CIU shock leads to a statistically significant decline in future industrial production and investment. The maximum estimated decline is slightly less than 1% for industrial production and 2% for investment.

[23] A one standard deviation shock to CIU raises the level of CIU by 0.53.

Local Projection Analysis

Next, we estimate responses of investment and output to inflation uncertainty using a local projection analysis (Jordà 2005). To mitigate endogeneity concerns, we use an instrument for inflation uncertainty: announcement surprises, defined as the absolute difference between economists' CPI forecasts (measured immediately before the release) and the actual number released. Formally, we define, for each month t, the Announcement Surprise CPI_t as the difference between year-on-year CPI inflation for month t and economists' forecasts right before the release. In Section 5, we show that CIU rises in response to these surprises. Here, we interpret it as a source of exogenous variation in inflation uncertainty and estimate its effects on investment and industrial production. Our regression specification is:

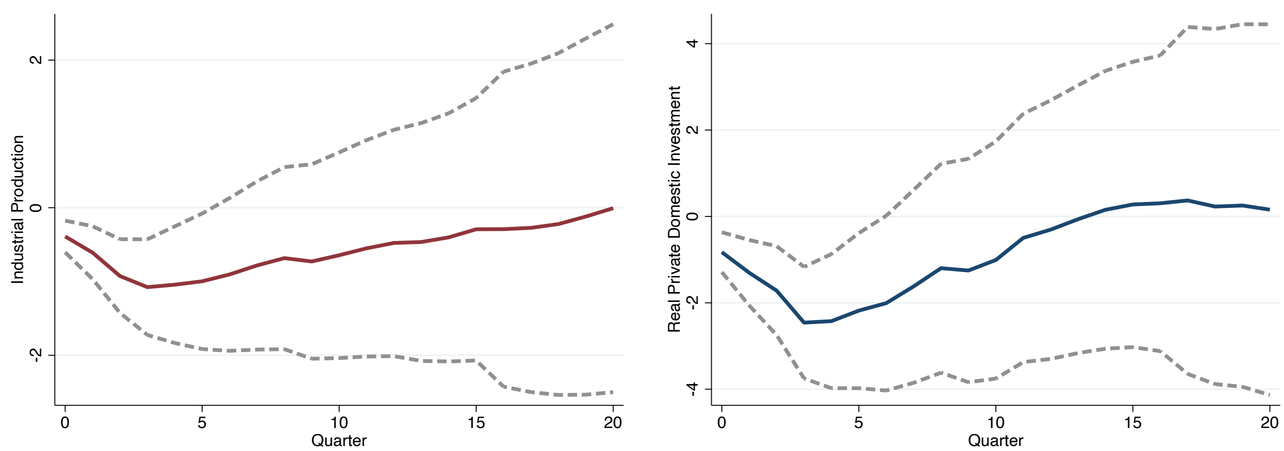
$$y_{t-1,t+h} = \beta_0 + \beta_1 \cdot \text{Announcement Surprise CPI}_t^2 + \epsilon_{t,h} \tag{11}$$

where y denotes the outcome variable of interest.

Figure 9: **Local projection: Response of investment & production to inflation uncertainty shock**

(A) Industrial production response to squared CPI surprise

(B) Investment response to squared CPI surprise



Note: This figure shows the impulse responses of industrial production (Panel A) and investment (Panel B) to inflation uncertainty shocks, estimated using (11) on quarterly data from 1980Q1 to 2025Q1. The gray lines show 90% confidence bands based on Newey-West standard errors with lag length $h + 1$.

Figure 9 shows the estimated impulse response of industrial production and investment to a one standard deviation inflation uncertainty shock, measured by Announcement Surprise CPI_t^2.[24] The findings are broadly in line with the VAR estimates above: a one standard deviation shock to inflation uncertainty leads to a drop in industrial production (investment) of about 1% (2%).

[24] To compare the magnitudes to the VAR analysis above, a one-standard-deviation movement of Announcement Surprise CPI_t^2 translates into a 0.55-point increase in CIU.

In summary, heightened inflation uncertainty significantly dampens economic activity: output and investment (by both households and firms) show persistent declines.

4.3 Disagreement on Interest Rates

Inflation is a key input into monetary policy and therefore an important driver of interest rates. Motivated by this link, we also examine the relationship between inflation uncertainty and interest rate disagreement. Prior studies emphasize the importance of belief disagreement in fixed-income markets (e.g., Xiong and Yan 2010; Ehling, Gallmeyer, Heyerdahl-Larsen, and Illeditsch 2018). We study two measures of disagreement. The first is the cross-sectional standard deviation of Blue Chip forecasts of the federal funds rate or the 10-year Treasury yield one quarter as well as four quarters into the future. The second measure is the range (high minus low) of Fed officials' forecasts of future federal funds rate published in the Summary of Economic Projections as the so-called "dot plot", which is widely followed by investors and has been shown to influence bond yields (Hillenbrand 2025).

Table 8 presents the results.[25] It shows that inflation uncertainty has very different effects on the two types of disagreement. CIU is positively related to professional forecasters' interest rate disagreement, though the relationship is notably weaker than with their disagreement about inflation. Interestingly, inflation uncertainty has the opposite effect on the Fed dot plots—the range of interest rate forecasts narrows during periods of high uncertainty about future inflation. One potential explanation is that the Fed adopts a tighter monetary policy stance in response to higher inflation uncertainty (Cieslak, Hansen, McMahon, and Xiao 2023) and reinforces this message by conveying alignment on future interest rates.

[25]The regressions also include a control for the zero lower bound period (ZLB) to capture the possibility of less disagreement when the ZLB binds.

Table 8: **Inflation Uncertainty and Interest Rate Disagreement**

	Blue Chip fed funds rate		Blue Chip 10y yield		FOMC Dot Plot		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	h=1Q	4Q	1Q	4Q	YE	1y YE	2y YE
Composite Inflation Uncertainty (CIU)	0.213**	0.248**	0.419***	0.324***	0.009	-0.033*	-0.045
	(2.49)	(2.22)	(5.86)	(3.70)	(1.03)	(-1.95)	(-1.49)
Zero lower bound	-1.145***	-1.151***	-0.847***	-0.903***	-0.044	0.004	0.128
	(-4.91)	(-3.60)	(-5.95)	(-3.33)	(-1.41)	(0.05)	(1.08)
Observations	461	461	425	425	53	53	53
R^2	0.252	0.263	0.245	0.212	0.054	0.041	0.138

Note: This table relates (standardized) interest-rate disagreement (dispersion across forecasters) to inflation uncertainty. The Blue Chip federal funds rate forecasts are available on a monthly basis from December 1984 to April 2023, while the 10-year bond yield forecasts become available in January 1988. The FOMC dot plot forecasts are available for every other FOMC meeting between January 2012 and March 2025. t-stats based on Newey-West standard errors are shown in parentheses. $h = 1$ ($h = 4$) denotes the forecast one quarter (one year) ahead for year-over-year inflation or the level of interest rates, while "YE" refers to forecasts for the end of the current year, with "1y YE" and "2y YE" indicating forecasts for the end of the next year and the year after, respectively. Significance levels: *(p<0.10), **(p<0.05), ***(p<0.01).

5 What Drives Inflation Uncertainty?

The significant effects of inflation uncertainty on financial markets and the real economy underscore the need to better understand the underlying driving factors. Prior work has made somewhat limited progress on this question.

One well-known hypothesis argues that higher *levels* of inflation are associated with greater uncertainty about future inflation (Okun 1971; Friedman 1977). This is often cited as a key motivation for keeping inflation at low/moderate levels. Theoretical explanations for the level-uncertainty link usually attribute it to monetary policy considerations. For example, in Ball (1992), higher inflation makes the public less certain about the central bank's responsiveness toward inflation. Relatedly, in Cukierman and Meltzer (1986), imperfect central bank credibility gives rise to a positive inflation level–uncertainty relationship. An alternative explanation for this link is related to attention to inflation. Pfäuti (2023) finds that households pay more attention to inflation at higher levels and that supply shocks have stronger and more persistent effects on inflation during periods of high attention. This is supported by the evidence in Weber, Candia, Afrouzi, Ropele, Lluberas, Frache, Meyer, Kumar, Gorodnichenko, Georgarakos, et al. (2025).

In this section, we use our inflation uncertainty series to conduct an empirical assessment of this hypothesis and the associated theories. We demonstrate a strong relationship between the level of inflation and uncertainty, providing support for this long-standing idea. However, we find that uncertainty also rises sharply when inflation is very low, suggesting that what matters is not the level *per se*, but its deviation from a target/reference.

We also document that large CPI announcement surprises—deviations of actual inflation from expectations—induce spikes in uncertainty. This suggests an important role for factors other than monetary policy—since it is unlikely that agents learn about the Fed's policy stance from CPI announcements.

To understand further drivers of inflation uncertainty, we conduct a topic analysis of the NY Times articles concerned with inflation uncertainty. Again, our results provide partial support for the Ball (1992) hypothesis, but also highlight the important role of other factors. While there are episodes when monetary policy factors are important for inflation uncertainty—such as the 1980s or the post-pandemic period—more generally, other factors emerge as very salient: in particular, uncertainty over supply conditions seems to have played a significant role over the whole sample. Unpredictability of consumer demand is particularly relevant during recessions. The procedure also identifies policy uncertainty—in particular, related to fiscal policy—as a notable contributor to inflation uncertainty.

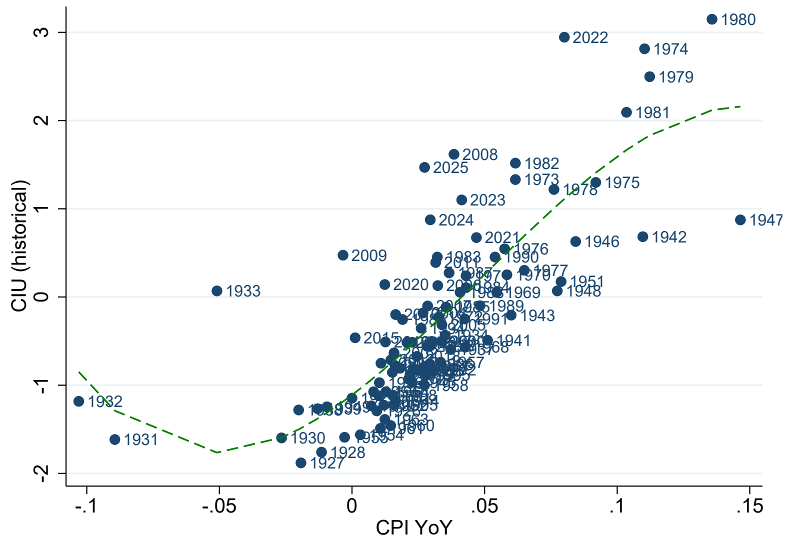
5.1 Inflation Uncertainty, Inflation Level and Announcement Surprises

To study the relationship between level and uncertainty of inflation, existing empirical research has generally relied on survey disagreement (Cukierman and Wachtel 1979) or time-series models (Ball, Cecchetti, and Gordon 1990; Grier and Perry 1998) as proxies of inflation uncertainty. The findings have been, by and large, inconclusive. Here, we revisit this classic question, using our arguably more direct measure of uncertainty and leveraging the length of our historical time series, which spans a wide range of observed inflation levels.

Figure 10 plots the level of inflation (measured by year-over-year change in CPI) against CIU. All variables are normalized. The graph shows a striking relationship: uncertainty is high at high levels of inflation and low at low levels, lending support to classical theories. Interestingly, when the level of inflation is near zero or even negative, inflation uncertainty rises again. This pattern suggests a somewhat more nuanced relationship between level and uncertainty: what matters for uncertainty is not the level *per se* but also the distance from a target or reference level.

We next present an empirical pattern suggesting that monetary policy is only part of the level-uncertainty link. Particularly, we show that inflation uncertainty is related to the size of announcement surprises, defined as the difference between economists' CPI forecasts (measured immediately before the release) and the actual number released. Arguably, the information that is learned from CPI announcements is orthogonal to Fed policy, which is more likely learned from statements and/or speeches released by the Fed. Following this idea, we define, for each month t, the Announcement Surprise CPI_t as the difference between year-on-year CPI inflation for month t and the economists' forecasts right

Figure 10: **Inflation Uncertainty vs Inflation Level**



Note: This figure compares inflation uncertainty with the level of inflation. The green line is the fit from a cubic polynomial. The sample period is from 1926 to 2025.

before the release. We then compute the cumulative squared surprises over the preceding 12 months:

$$\overline{\text{Surprise}_t^2} = \sum_{s=t-11}^{t} \text{Announcement Surprise CPI}_s^2. \tag{12}$$

The announcement forecast data are obtained from Money Market Services (MMS) prior to 2005 and from Bloomberg from 2005 onwards. Appendix Figure H.14 plots both the $\overline{\text{Surprise}_t^2}$ series along with the CIU. The graph shows a clear positive association between uncertainty and CPI surprises, especially during the large swings, such as the early 1980s, the GFC or the post-pandemic period.

To test the relationship between inflation uncertainty and CPI announcement surprises more formally, we estimate the following regression:

$$CIU_t = \beta_0 + \beta_1 \cdot \overline{\text{Surprise}_t^2} + \varepsilon_t. \tag{13}$$

Table 9 presents the estimates. Column (1) shows that uncertainty rises when CPI deviates significantly from expectations. The R^2 is high: squared CPI surprises explain about 43% of the variation in CIU, comparable to the explanatory power of the inflation level alone. The coefficient on squared CPI surprises decreases modestly when we add the level of inflation (column (3)), as well as the mean of "raw" CPI surprises over the past twelve months and the squared inflation level, to account for the non-linearities highlighted in Figure 10. Columns (5) to (7) include other macro-announcement surprises. Interestingly, the coefficients on almost all of these are insignificant, and they add little explanatory power.

Table 9: **Inflation Uncertainty and CPI Announcement Surprises**

	CIU						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
12month CPI squared surprises	0.655***		0.413***	0.337***	0.586***	0.512***	0.255***
	(6.23)		(5.90)	(4.44)	(5.13)	(6.05)	(3.65)
CPI YoY		0.756***	0.538***	0.320**			0.576***
		(6.60)	(5.45)	(2.06)			(3.82)
12month CPI surprises				0.266***			0.227***
				(5.58)			(4.11)
Squared CPI YoY				0.166			-0.068
				(0.86)			(-0.44)
12month Retail sales squared surprises					-0.075	-0.014	-0.040
					(-0.63)	(-0.12)	(-0.74)
12month Industrial production squared surprises					0.115	0.131	0.192***
					(0.77)	(0.91)	(2.80)
12month Housing starts squared surprises					0.125*	0.122	0.035
					(1.74)	(1.50)	(0.74)
12month Unemployment squared surprises						0.086	0.017
						(1.06)	(0.36)
Observations	538	538	538	538	538	514	514
R^2	0.429	0.486	0.616	0.671	0.444	0.453	0.718
Sample						Excl. Covid	Excl. Covid

Note: This table relates inflation uncertainty to the sum of squared CPI announcement surprises over the past twelve months, following eq. (13). We use the CPI announcement surprises from Money Market Services (MMS) until 2004 and from Bloomberg starting in 2005. The sample period is from June 1980 to March 2025. All variables are standardized. Significance levels: *(p<0.10), **(p<0.05), ***(p<0.01).

Overall, this suggests that CPI surprises convey substantial information about inflation uncertainty. They also indicate that announcement surprises can be used as an instrument for movements in inflation uncertainty—a strategy we have exploited in Section 4 when studying the consequences of elevated uncertainty. The evidence is also consistent with surprises being perceived as signals of regime shifts or other structural changes, which may induce greater uncertainty. We examine this possibility next by using topic analysis to explore the underlying drivers of fluctuations in inflation uncertainty.

5.2 Topic Analysis

Next, we use the LLM to probe deeper into the content of the articles flagged as related to inflation uncertainty. Our analysis can be seen as an LLM-based topic analysis. We proceed in several steps. First, we ask ChatGPT to identify (for each flagged article) "the key factor causing inflation uncertainty" (see Q3 in Figure 5 showing our ChatGPT Prompt). In the second step, we prompt ChatGPT to list 10 broad "topics" from the set of factors in the previous step. This procedure yields the following list of topics:[26] (1) Supply chain and production issues; (2) Energy, commodity, and agricultural product prices; (3) Labor market and wage issues; (4) Trade policies and international relations; (5) Government fiscal policies and budgeting; (6) Monetary policy and interest rates; (7) Consumer demand and retail sales; (8) Economic growth; (9) Stock market and financial volatility; and (10) Housing market. Third, we ask ChatGPT to assign the factor from each article, or equivalently the underlying article, to one of these 10 topics. Fourth and finally, we then classify the LLM-selected topics into six overarching categories: (i) "demand" consisting of the topics "economic growth" and "consumer demand and retail sales", (ii) "supply" consisting of the topics "supply chain and production issues", "energy, commodity, and agricultural product prices" and "labor market and wage issues", (iii) "monetary policy" consisting of the topic "monetary policy and interest rates", (iv) "fiscal policy" comprising the topic "government fiscal policies and budgeting", (v) "trade policy" reflecting the topic "trade policies and international relations", and (vi) " financial" consisting of the topics "stock market and financial volatility" and "housing market".

Table 10: **Descriptive Statistics of Topic Analysis**

	Fraction (%)				Fraction (%)	
Topic	mean	sd	Peak Month	Category	mean	sd
Energy and commodity prices	28	21	1990m8	Supply	41	20
Labor market and wage issues	9	7	2014m8			
Supply chain and production issues	4	6	2021m10			
Monetary policy and interest rates	27	16	1984m5	Monetary Policy	27	16
Economic growth	12	8	2017m5	Demand	17	9
Consumer demand and retail sales	4	4	2020m7			
Government fiscal policies and budgeting	6	7	2020m11	Fiscal Policy	6	7
Trade policies and international relations	5	9	2025m3	Trade Policy	5	9
Stock market and financial volatility	2	3	1997m12	Financial	4	5
Housing market	2	4	2006m12			

Note: This table provides an overview of the fraction of inflation-uncertainty-related articles that can be assigned to a specific topic and category. We apply a two-(three-)step procedure for the topic (category) assignment. First, we ask ChatGPT about the "key factor causing inflation uncertainty" for each inflation-uncertainty-related article. Second, we ask ChatGPT to assign each identified factor to a topic from our list of ten topics. Third, the topics are grouped into overarching categories. Topic labels are slightly abbreviated for legibility. The percentages are calculated after removing factors/articles that cannot be assigned to any topic. This affects on average 14% of all articles over the full sample period.

Table 10 and Panel A of Figure 11 show that supply-related topics are the dominant drivers of inflation uncertainty in our topic analysis. In 41% of inflation-uncertainty-related articles, ChatGPT identifies

[26] We made some minor adjustments to the exact descriptions of the topics to aid interpretation.

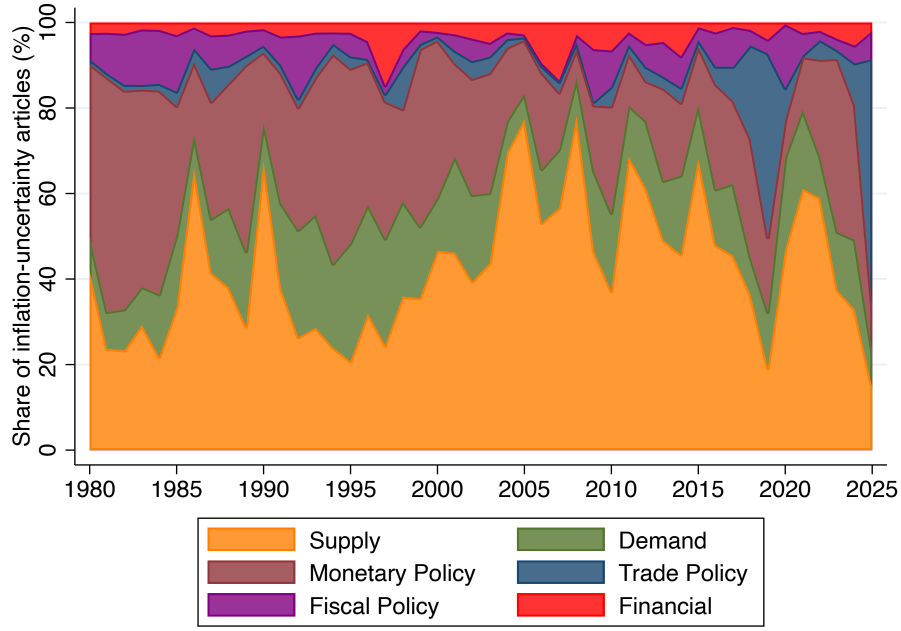
supply-side issues as the primary source of uncertainty, with "energy and commodity prices" and "labor market and wage issues" singled out as the key driver in 28% and 9% of articles, respectively. The topic "energy and commodity prices" accounted for its highest share of articles in August 1990, coinciding with the Iraqi invasion of Kuwait and the associated surge in oil prices. Consistent with theories that link monetary policy actions and credibility to inflation uncertainty (e.g., Ball 1992; Cukierman and Meltzer 1986; Evans and Wachtel 1993), we also find that monetary policy is frequently cited as an important driver of uncertainty about future prices. The topic "monetary policy and interest rates" is the second-largest category in our classification, appearing in 27% of articles. Its prevalence peaks in the early 1980s, coinciding with the Volcker disinflation, and then declines steadily before spiking again in the post-pandemic period. Third in importance are demand-based factors, with economic growth and consumer demand identified as the primary source of inflation uncertainty in 15% and 6% of articles, respectively. Financial factors play a smaller role overall, though the share of articles assigned to the "housing market" category peaked in late 2006, at the onset of the subprime mortgage crisis. Fiscal and trade policy contributions are generally modest but volatile, rising sharply during key policy inflection points, as discussed below.

Panel B of Figure 11 zooms in on the COVID-19 era, focusing on the 2018-2025 period. In 2018-19, trade policy was a key driver of inflation uncertainty. This changed with the outbreak of the pandemic. As the pandemic-related restrictions were lifted and consumer demand normalized, supply chains remained under stress, contributing significantly to inflation uncertainty. The unusual nature of demand conditions (e.g. shifts in spending patterns from services to goods, the extraordinary size of fiscal stimulus) also made inflation harder to forecast—see, e.g. Giannone and Primiceri (2024). The role of supply peaked around late 2021 and early 2020, amid supply-chain disruptions and Russia's invasion of Ukraine. As these forces dissipated and the Fed started aggressively raising interest rates, factors related to monetary policy emerged as key drivers of inflation uncertainty. Finally, in 2025, inflation uncertainty seems to be once again driven by trade policy. At the end of our sample in March 2025, shortly before the tariff announcement by the Trump administration, tariffs became the all-dominant driver of inflation uncertainty.

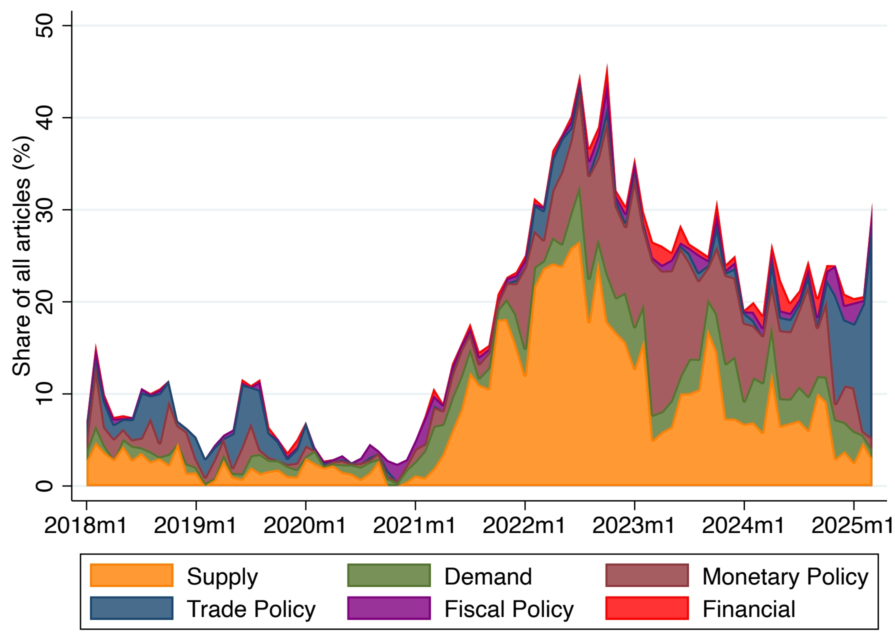
Alternative Textual Factor Analysis In Appendix J, we take another approach to uncovering the drivers of inflation uncertainty by relating it to the time series of uncertainty about specific topics (demand, supply, fiscal and trade policy). These series are constructed by prompting the LLM to assess the degree of uncertainty about the corresponding topic in individual NYT articles. The results show that, as in the topic analysis, supply-related uncertainty is the most important driver of inflation uncertainty.

Figure 11: **News Topic Analysis: What Drives Inflation Uncertainty?**

(A) 1980–2025



(B) 2018–2025



Note: This figure shows the fraction of inflation-uncertainty-related articles assigned to a specific topic. We use a two-step procedure. First, we ask ChatGPT about the "key factor causing inflation uncertainty" in each article, see Q3 of the prompt shown in Figure 5. Second, we ask ChatGPT to assign the factors to one out of 10 topics. Panel A focuses on the full sample from 1980 to 2025 and plots the annual share of inflation-uncertainty articles devoted to each topic. Panel B focuses on the pandemic period (January 2018 to March 2025) and plots the monthly share of all articles devoted to each topic. The percentages are calculated after removing factors/articles that cannot be assigned to any topic. This affects on average 14% of all articles over the full sample period and 12% of articles over the COVID period.

Demand-related uncertainty is more cyclical, becoming salient during recessions, in line with standard macroeconomic theory. Fiscal policy uncertainty also contributes meaningfully in some episodes, while trade policy plays a more limited role. These patterns closely mirror those uncovered in the topic analysis, lending credibility to the LLM-based classification approach. Taken together, the evidence reinforces the idea that inflation uncertainty is shaped by a broad set of factors—not only monetary policy, but also the uncertainty about supply, demand and economic policy.

5.2.1 Does the Driving Factor Matter for the Effect of Inflation Uncertainty?

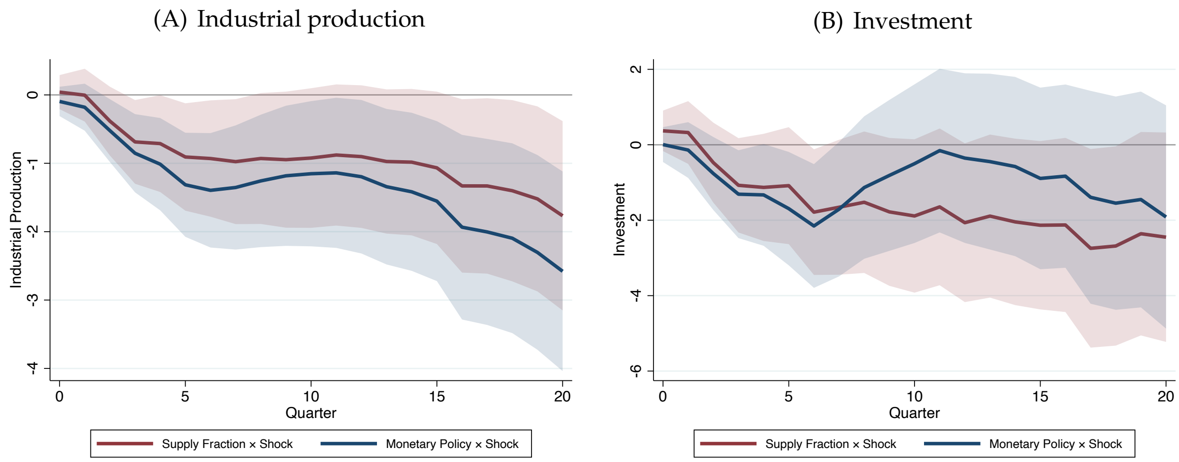
Next, we explore the extent to which the consequences of inflation uncertainty documented in Section 4 vary depending on the factor driving the change in uncertainty. Specifically, we run the following extended version of the local projection specification in Equation (11):

$$\begin{aligned}
y_{t-1,t+h} = \beta_0 &+ \beta_1 \cdot |\text{Announcement Surprise CPI}_t| \\
&+ \beta_2 \cdot |\text{Announcement Surprise CPI}_t| \cdot \text{Fraction}_t(\text{Supply}) \\
&+ \beta_3 \cdot |\text{Announcement Surprise CPI}_t| \cdot \text{Fraction}_t(\text{Monetary Policy}) \\
&+ \beta_4 \cdot \text{Fraction}_t(\text{Supply}) + \beta_5 \cdot \text{Fraction}_t(\text{Monetary Policy}) + \epsilon_{t,h}
\end{aligned}$$

where $\text{Fraction}_t(\text{Supply})$ and $\text{Fraction}_t(\text{Monetary Policy})$ are, respectively, the fractions of articles assigned to the categories of Supply and Monetary Policy at time t. The coefficients of interest are β_2 and β_3, which index the incremental effect of the corresponding category on the outcome variable. Figure 12 plots these coefficients for industrial production (left panel) and investment (right panel). Overall, it shows mostly insignificant effects from the interaction term.[27] In other words, regardless of the driving factor, inflation uncertainty has broadly similar implications for output and investment. This is suggestive of more direct channels (like the cost of capital effects highlighted in the previous section) relative to more indirect mechanisms.

[27] The only significant estimates are for monetary policy on output.

Figure 12: **Effect of Inflation Uncertainty by Category**



Note: This figure shows the response of industrial production (Panel A) and investment (Panel B) to inflation uncertainty shocks, decomposed by the underlying driving factor. The plotted coefficients are β_2 and β_3 from the local projection specification above — the incremental response associated with a one-standard-deviation increase in the share of articles attributing inflation uncertainty to supply factors (Supply Fraction $\times$ Shock, maroon) or monetary policy (Monetary Policy $\times$ Shock, navy), respectively. Estimation uses quarterly data from 1980Q1 to 2025Q1, with the squared CPI announcement surprise as the shock. The shaded areas show 90 percent confidence bands based on Newey-West standard errors with lag length $h + 1$.

6 Conclusion

In this paper, we conducted a comprehensive analysis of inflation uncertainty in the United States. Our novel measures, which combine textual analysis of news articles as well as information from asset prices, extend as far back as 1900, and line up well with survey-based and other uncertainty measures when the latter are available. We leverage the length of our sample to shed new light on the drivers of inflation uncertainty, including demand, supply and policy factors. We document that inflation uncertainty has significant macro and financial implications, highlighting the differential impact on real and nominal assets, equity and bond claims on business assets, investment and output.

There are a number of avenues for future research. An obvious one is to use our approach to construct inflation uncertainty measures for other countries. Our results on the effects of inflation uncertainty raise several interesting questions. Understanding the variation in impact, both across assets and over time, is an important next step. On the macro front, more work is needed to parse out the different mechanisms through which uncertainty impacts household and firm decisions (e.g., Georgarakos, Gorodnichenko, Coibion, and Kenny 2024; Kostyshyna and Petersen 2024). The role of inflation credibility of monetary policy as a driving force behind inflation uncertainty (see Acharya, Hillenbrand, and Venkateswaran 2025) is another important direction for more research.

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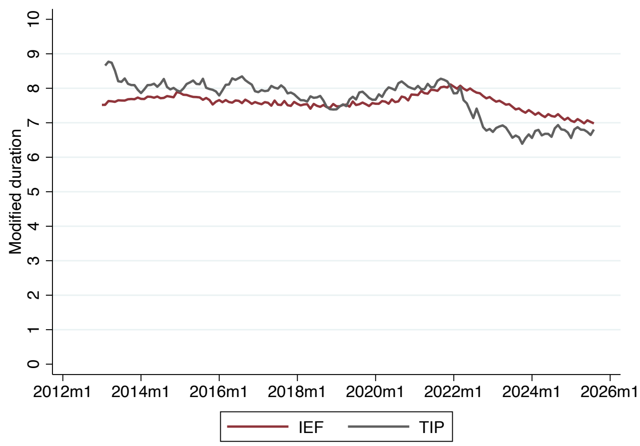
APPENDIX

A Market-based Inflation Uncertainty – Additional Information

A.1 Duration and Nominal-Real Correlation

Figure A.1: **Modified Duration of Bond ETFs**



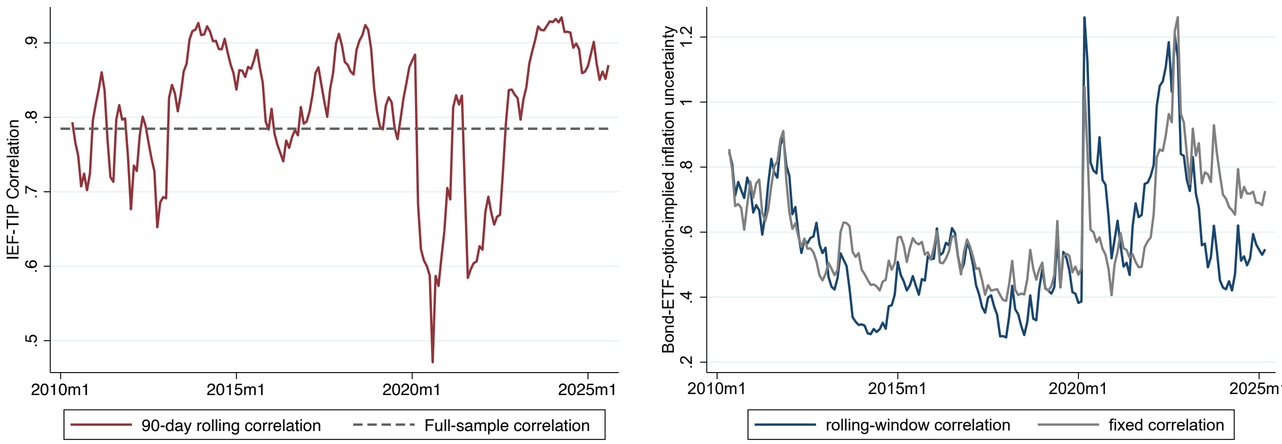
Note: This figure plots the modified duration of the iShares 7-10 Year Treasury Bond ETF (IEF, maroon line) and the iShares TIPS Bond ETF (TIP, gray line) over time. Modified duration measures the approximate percentage change in the ETF price for a one percentage point change in yields and is used to convert option-implied price volatility into yield volatility.

Figure A.2 explores the robustness of our estimates to assumptions about the correlation between real and nominal rates. Our baseline specification (the darker navy line) uses the observed correlation of ETF returns over a rolling 90-day window, while the other uses a fixed correlation for the whole sample.

Figure A.2: **Robustness: Correlation between nominal and real interest rates**

(A) Correlation IEF-TIP

(B) Inflation Uncertainty under different correlation assumptions



Note: This figure explores the robustness of our inflation uncertainty measure to different assumptions about the correlation between real and nominal rates. Panel A plots the correlation between the daily total returns of the iShares 7-10 Year Treasury Bond ETF (IEF) and the iShares TIPS Bond ETF (TIP). The darker line shows the realized correlation computed over a rolling 90-day window, capturing time variation in the co-movement between nominal Treasury and TIPS returns, while the gray line shows the unconditional correlation estimated over the full sample period. Panel B compares the implied inflation uncertainty from ETF options under these two correlation assumptions: the darker line uses the rolling 90-day realized correlation, while the gray line uses the full-sample unconditional correlation.

A.1.1 TIPS Cashflows and Inflation Volatility

The principal on TIPS tracks realized inflation with a 3-month lag:

$$Princ_s = \frac{RefCPI_s}{RefCPI_{IssueDate}} \quad \text{where} \quad RefCPI_s \equiv CPI_{s-3m} \,. \tag{A.1}$$

The price at time t of a T-maturity TIP (per \$100 of principal at issue) is the discounted sum of cashflows, i.e.

$$P_t^{TIP} = 100 \sum_{s=1}^{T} DF_{t,s} \cdot Princ_s \cdot Coupon \qquad \text{where} \tag{A.2}$$

$$DF_{t,s} \equiv \text{Nominal discount factor at } t \text{ for date } s = \frac{CPI_t}{CPI_s} \frac{1}{(1+r_{t,T})^s} \,, \tag{A.3}$$

$$r_{t,T} \equiv \text{Real interest rate at } t \text{ for maturity} T \,, \tag{A.4}$$

$$\Rightarrow \quad P_t^{TIP} = 100 \frac{CPI_t}{RefCPI_{IssueDate}} \sum_{s=1}^{T} \frac{CPI_{s-3m}}{CPI_s} \frac{Coupon}{(1+\text{RealRate}_{t,T})^s} \,. \tag{A.5}$$

In other words, the small lag in tracking inflation leads to an adjustment factor, capturing realized inflation over the lag $\frac{CPI_{s-3m}}{CPI_s}$. If inflation is assumed to shift in parallel, this factor is proportional to inflation. This allows us to approximate the change in (the log of) the bond price as:

$$\Delta \ln P_t^{TIP} \approx -Dur^{TIP} \cdot \Delta r_{t,T} - \frac{1}{4} \cdot \Delta \pi^e_{t,T} \,. \tag{A.6}$$

Using this approximation, we can express implied volatility of expected inflation as a function of three moments of the returns on nominal and real bonds:

$$\sigma_{\pi^e} = \frac{Dur}{Dur - 0.25} \sqrt{\sigma^2_{Nom} + \sigma^2_{TIP} - 2 \cdot \rho_{Nom,TIP} \;\; \sigma_{Nom} \;\; \sigma_{TIP}} \qquad \text{where} \tag{A.7}$$

$$\sigma_{Nom} = \text{Implied volatility of nominal bond returns}/Dur \,, \tag{A.8}$$

$$\sigma_{TIP} = \text{Implied volatility of real bond returns}/Dur \,, \tag{A.9}$$

$$\rho_{Nom,TIP} = \text{Correlation of nominal and real bond returns} \,. \tag{A.10}$$

This implies that ignoring the lag (as we do in the main text) understates inflation volatility by a factor $\frac{Dur}{Dur-0.25}$. For the ETFs used in this paper, $Dur = 7.8$, so the adjustment factor becomes

$$\frac{Dur}{Dur - 0.25} = 1.03 \,.$$

Thus, the bias from ignoring the lag is quantitatively very small and more importantly, does not affect the interpretation of the time series patterns or the regression results.

A.2 Option-Implied Commodity Volatilities

In the following, we describe our procedure to calculate the implied volatility of 3-month at-the-money options on commodity futures. Our approach follows the CME methodology.

The calculation first begins by finding the strike that is closest to the future value and has a value for both the call and put. This strike is then used to create the synthetic future which is the strike plus the difference between the call value and the put value for the strike. After finding the synthetic future price, the data is cleaned. All strikes are removed if the settlement value for either the call or put is 0. Furthermore, if the sum of the settlement value of the calls of any three consecutive strikes is equal to zero, then all strikes greater than the lowest strike are removed. Similarly, if the sum of the settlement value of the puts of three consecutive strikes is 0 then all the strikes below the highest strike are removed.

Following this cleaning the option value for the ATM option is calculated. In case the synthetic future is an existing strike, the average of the call and put value is used. If the synthetic future is not an existing strike, then the following formula is used:

$$O_{O_N} = \frac{0.5 \cdot (F - K_{-1}) \cdot (C_{K_{+1}} + P_{K_{+1}}) + 0.5 \cdot (K_{+1} - F) \cdot (C_{K_{-1}} + P_{K_{-1}})}{K_{+1} - K_{-1}} \tag{A.11}$$

In the above K_{+1} is the strike immediately above the synthetic future strike whereas K_{-1} is the strike immediately below the synthetic future strike. C and P refer to the value of the calls and puts respectively. F is the futures price. O_{O_N} denotes the at-the-money (ATM) option premium for the tenor N, which for our purposes is usually three months.

This option value is then used to calculate the at-the-money (ATM) option volatility for the future in the following:

$$ATM_N = 100\sqrt{\frac{2\pi}{T_N}} \cdot \frac{O_{O_N}}{F_N} \tag{A.12}$$

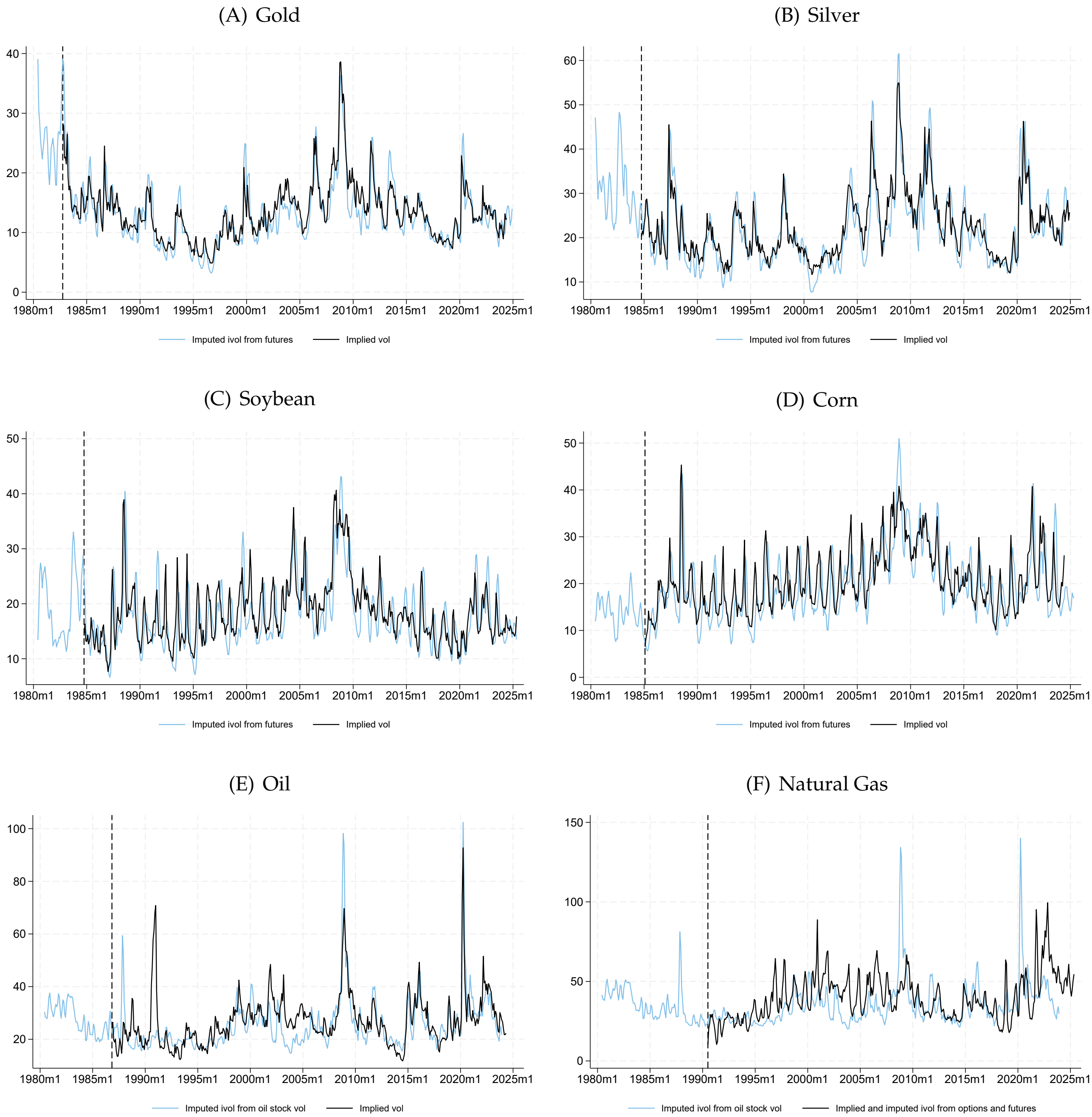
Where T_N is number of years between the trade date and the underlying future's expiry date, and F_N is the synthetic strike value. Using this ATM vol, we use the 3m volatility whenever available. However, as there is not always a 3m futures outstanding, we interpolate between the two futures that are closest (e.g. 2m and 4m if available) in such case using the following calculation:

$$\widehat{ATM}_N = \sqrt{\frac{\left((T_h - 0.25) \cdot ATM_l{}^2\right) + \left((0.25 - T_l) \cdot ATM_h{}^2\right)}{T_h - T_l}} \tag{A.13}$$

Where h denotes the shortest forward that is more than 3m and l denotes the forward that is the longest forward that is shorter than 3m.

When option-implied volatility is not available, then we calculate realized volatility from commodity futures as the standard deviation of a rolling three-month window as the futures expiring in three months (3m future). If the 3m future is not available, we will compute the realized volatility of the 2m and the 4m futures and then linearly interpolate between the volatilities of the 2m and the 4m futures. Additionally, we use CRSP data to calculate the volatility over a 3-month window for daily stock returns for all companies with the SIC code 1311 (crude petroleum and gas). We then create a weighted mean

Figure A.3: **Option-Implied Commodity Volatility**



Note: This figure shows the option-implied volatility of commodity futures extracted from 3m at-the-money options on commodity futures. When the option data is unavailable, we use the 90-day realized volatility of the 3-month futures contract for gold, silver, soybean and corn, and use the 90-day realized stock price volatility for stocks in the oil and gas industry for oil and natural gas.

where we weight the volatility by the firm's market capitalization.

A.3 Summary Statistics

Table A.1: Summary Statistics for Market-based Variables

Panel A: Commodity Price Volatility

	ETF Sample 2010m5–2023m8		Main Sample 1980m6–2025m3		Principal Component Weights		
	Mean	Standard Deviation	Mean	Standard Deviation	PC1	PC2	PC3
Gold	11.53	3.06	12.71	5.57	0.48	0.03	-0.16
Silver	18.97	6.17	20.93	8.07	0.48	0.06	-0.2
Soybean	15.1	3.59	16.56	5.5	0.44	-0.39	0
Corn	19.36	6.12	17.6	6.19	0.44	-0.38	-0.03
Oil	24.95	11.36	24.67	9.44	0.33	0.4	0.85
Natural Gas	33.11	11.39	35.24	11.83	0.22	0.74	-0.45

Panel B: Predictor Variables

	ETF Sample 2010m5–2025m3		Main Sample 1980m6–2025m3	
	Mean	Standard Deviation	Mean	Standard Deviation
Commodity ivol PC1	-0.54	1.33	-0.53	1.56
Commodity ivol PC2	0.02	1.17	-0.02	1.03
Commodity ivol PC3	-0.1	0.77	-0.14	0.89
CPI yoy	0.03	0.02	0.03	0.02
5y inflation swap (iswap)	2.12	0.46	2.22	0.53
30-day rvol 5y iswap	0.51	0.23	0.62	0.4

Note: This table provides summary statistics for market-based variables. Panel A focuses on the price volatility of various commodities. Panel B focuses on the variables used in the prediction model to predict bond-ETF-option-implied volatility.

A.4 Robustness: Prediction in Changes

Table A.2: Prediction Model for Market-based Inflation Uncertainty – Changes

	Δ Inflation implied vol - ETFs					
	(1)	(2)	(3)	(4)	(5)	(6)
Δ CME PC1	0.093***		0.098***	0.081***	0.064***	
	(0.016)		(0.018)	(0.020)	(0.012)	
Δ CME PC2	0.037***		0.040***	0.034***	0.024*	
	(0.010)		(0.011)	(0.013)	(0.013)	
Δ CME PC3	-0.040***		-0.041***	-0.036**	-0.030***	
	(0.014)		(0.015)	(0.014)	(0.006)	
Δ CPI yoy		0.005	0.061**	0.053	0.048***	
		(0.068)	(0.030)	(0.034)	(0.018)	
Δ 5y inflation swap (iswap)				-0.004	0.007	
				(0.014)	(0.013)	
Δ 30-day rvol 5y iswap				0.023**	0.016	
				(0.011)	(0.015)	
Δ $\widehat{\text{Inflation ivol}}_t^{ETF}$						0.799***
						(0.137)
Observations	176	176	176	166	166	176
R^2	0.543	0.000	0.572	0.591	0.496	0.555
Correlation	Roll	Roll	Roll	Roll	Fixed	Roll

Note: This table shows the results of estimating the predictive model given in eq. (8) in 3-month changes. All x-variables have been standardized to a mean of zero and a standard deviation of one. t-statistics based on Newey-West standard errors are shown in parentheses. Significance levels: *(p<0.10), **(p<0.05), ***(p<0.01).

B News-based Inflation Uncertainty – Additional Information

B.1 Comparison: Naive vs LLM Count Measures

Our count measure leverages generative AI to identify articles related to inflation uncertainty. This approach differs from traditional count measures, which select articles based on the presence of words from a predefined list. An advantage of the LLM-based measure is its ability to infer from the article's context whether it signals elevated inflation uncertainty. Figure B.4 illustrates this distinction using a few example articles. The texts of these articles do not contain keywords like uncertainty, so they would not be flagged under traditional count measures. Nevertheless, they appear related to inflation uncertainty.

Figure B.4: **Examples of articles**

Fed Official On Inflation, 1990-05-02:
A Federal Reserve governor, John P. LaWare, said today that the nation's high inflation rate in the first quarter might have been an aberration."Food, energy and apparel had up-blips and shouldn't continue," Mr. LaWare said in an interview at a meeting here of the Bankers Association for Foreign Trade."The labor cost increase was a little worrisome."The Government previously reported that consumer prices rose five-tenths of a percent in March, which translated to an 8.5 percent gain in the first quarter.Mr. LaWare said he hoped inflation would be almost unchanged in 1990, "but the signals are mixed." Last year, consumer prices rose 4.6 percent, after a 4.4 percent gain in 1988.A report by the Commerce Department showed that the economy grew at an annual rate of 2.1 percent in the first quarter. "I think we will see a continuation of slow, steady growth," Mr. LaWare said. "I think this slow, steady growth is very healthy under the circumstances."

Fed Ponders Inflation 'Night and Day,' Fed Chair Tells Lawmakers, 2021-07-15:
Jerome H. Powell acknowledged to a House committee on Wednesday that "the incoming inflation data have been higher than expected and hoped for."When Jerome H. Powell, the Federal Reserve chair, appears before the Senate Banking Committee on Thursday, he will be testifying at a fraught moment both politically and economically, given the recent rise in inflation.The Consumer Price Index jumped 5.4 percent in June from a year earlier, the biggest increase since 2008 and a larger move than economists had expected. Price pressures appear poised to last longer than policymakers at the White House or Fed anticipated.In testimony on Wednesday before the House Financial Services Committee, Mr. Powell attributed rapid price gains to factors tied to the economy's reopening from the pandemic, and indicated in response to questioning that Fed officials expected inflation to begin calming in six months or so.He acknowledged that "the incoming inflation data have been higher than expected and hoped for," but he said the gains were coming from a "small group" of goods and services directly tied to reopening.For now, he voiced comfort with the central bank's relatively patient policy path even in light of the hotter-than-expected price data. He said that the labor market was improving but that "there is still a long way to go."He also said the Fed's goal of achieving "substantial further progress" toward its economic goals before taking the first steps toward a more normal policy setting "is still a ways off."

Several Refiners Raise Fuel Prices, 1981-01-30:

Several major refiners raised wholesale fuel prices yesterday, a day after President Reagan ended price controls in the oil industry eight months ahead of schedule.The largest increase was posted by the Standard Oil Company of California, the nation's fourth-largest oil company.Major U S oil refiners raise wholesale fuel prices following President Reagan's decision to end price controls in oil industryIts ChevronUSA division raised wholesale gasoline prices 6 cents a gallon and heating and diesel fuel prices 5 cents a gallon. A Chevron spokesman said the rise was "necessary because of the increased costs of crude oil resulting from the Government's decontrol program."Other refiners increasing wholesale prices by one-half cent to 3 cents a gallon, depending on region and fuel type, included the Exxon Corporation, the Mobil Corporation, the Shell Oil Company and the Sun Company.Exxon raised wholesale prices of gasoline, home heating oil and diesel and jet fuel as much as 3 cents a gallon. Shell raised heating oil and diesel fuel prices 1 cent a gallon west of the Rockies and 3 cents a gallon elsewhere.Shell and Sun said their moves did not result from the President's action. Exxon said its rise reflected past increases in the cost of crude oil. Major U S oil refiners raise wholesale fuel prices following President Reagan's decision to end price controls in oil industry

Markets recoil as investors react to higher-than-expected inflation, 2022-06-10:

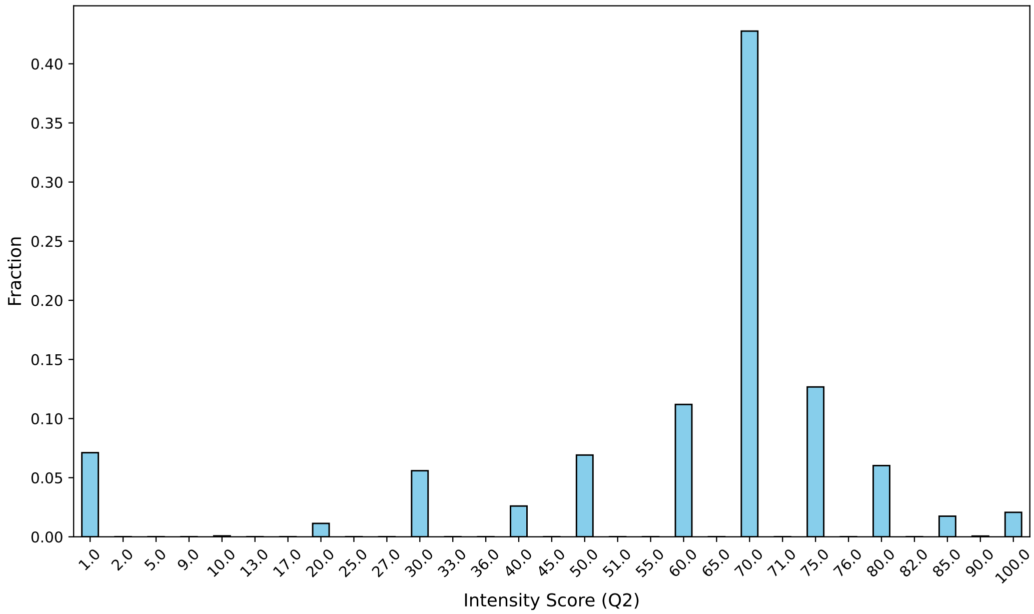
The inflation data indicated that policymakers would need to continue their aggressive attempts to slow the economy. The inflation data indicated that policymakers would need to continue their aggressive attempts to slow the economy.Stocks tumbled and bond yields jumped after consumer price data for May showed a higher-than-expected surge in inflation, indicating that policymakers would need to continue their aggressive attempts to slow the economy.The S&P 500 fell 2.9 percent on Friday. Yields on short-term government bonds, which serve as benchmarks for borrowing costs, rose sharply. The two-year Treasury note rose above 3 percent.For investors, the critical question was whether the inflation data would spur the Federal Reserve to raise interest rates higher or more quickly than expected, and what the rapid rise in borrowing costs could mean for the economy. The central bank is expected to raise its benchmark rate by half a percentage point next week.It would be "a massive surprise" if the Fed didn't raise interest rates by a half-point in July, Jim Reid of Deutsche Bank wrote in a morning note, so the market's main reaction would come from investors reassessing the size of a September increase based on the details in the inflation report.The S&P 500 dropped 2.4 percent on Thursday, its largest daily decline in about three weeks. The index ended the week with a drop of more than 5 percent, its worst showing since late January.Those losses mean that the index is now down 18.7 percent from its Jan. 3 record, bringing it back within reach of bear-market territory — a drop of 20 percent from a high — which signals a serious shift in investor sentiment on Wall Street. The index briefly dipped into bear territory , before recovering and closing just above that psychologically significant level.

A Tough Search for Workers as Hiring Lags Job Openings, 2016-01-13:

United States job openings rose in November and employers appeared to have trouble finding qualified workers, a trend that could prompt a pickup in wage growth this year. Job openings, a measure of labor demand, increased 82,000 to a seasonally adjusted 5.43 million, the Labor Department said on Tuesday in its monthly Job Openings and Labor Turnover Survey. The rise lifted the jobs openings rate to 3.7 percent from 3.6 percent in October. Hiring rose to 5.2 million from 5.17 million the month before, continuing to lag job openings. The hiring rate was unchanged at 3.6 percent. Job openings are high relative to the unemployment rate of 5 percent. "We interpret this as a sign of a mismatch between the needs of employers and the skills of job seekers," said John Ryding, chief economist at RDQ Economics in New York. The so-called Jolts report is among the data watched by Fed officials to get a pulse on both the labor market and inflation.

B.2 Distribution of Intensity Scores

Figure B.5: **Article-level distribution of intensity scores**



Note: This figure shows the distribution of article-level intensity scores (Q2) for all articles that are related to inflation uncertainty (Q1 = "Yes").

B.3 LLM Human Audit: Additional Information

This section describes the human audit of the LLM. Figure B.6 presents the instructions given to the auditors (which contained a number of examples of text from the articles in our sample). Figure B.7 compares the LLM intensity scores with the average intensity score assigned by human auditors. Figure B.8 compares the human and LLM scores for a couple of examples.

Figure B.6: **Guidelines for Human Auditors**

Instruction for rating articles related to inflation uncertainty

The articles to be rated were all flagged as being related to inflation uncertainty by ChatGPT. They are collected in an excel spreadsheet as well as in a pdf. Both are the same, but you might prefer to read the articles on the pdf (potentially using a printout version or Ipad). **Please record your answers in the excel spreadsheet.**

Question: For each article, answer the following multiple-choice question:

How stable/uncertain is inflation according to the article?

(a) High
(b) Medium-High
(c) Medium
(d) Medium-Low
(e) Low

Guidelines:

Imagine that you have to make a forecast for the consumer prices index (inflation). We are interested in the **uncertainty** surrounding that forecast. Specifically, does the article make you more or less certain about inflation? Does it change your outlook on how stable future inflation is expected to be?

- Uncertainty could reflect the risk of inflation being higher or lower than expected.
- Sometimes, the article might contain information that is about the **level** of inflation (e.g. whether is expected to rise or fall). This could also have implications for uncertainty, since inflation tends more volatile at higher levels.
- For other factors (monetary policy, GDP, labor market conditions, financial conditions etc.), try to assess whether the information presented indicates high/medium/low inflation uncertainty. E.g. high uncertainty about GDP may or may not translate to high inflation uncertainty: form the best assessment you can based on the content of the article (and your own understanding of macroeconomics).
- Evaluate each article on its own, try your best not to use information that is outside of the article.
- Many articles are collections of multiple news stories. Base your answer on the most relevant one.
- Some articles are about countries other than the US. In such cases, answer the question from the perspective of that country, i.e. indicate whether the article increases or decreases uncertainty about inflation in that country.
- If the country is about two countries, base your answer on the country the article is primarily about.
- If the connection between the information presented in the article and inflation strikes you as very remote, answer Low.
- In addition to your rating, state your rationale. This doesn't have to be long – a few words, a key phrase or two from the article or a one sentence summary should be sufficient. You may also find it helpful to highlight key sentences in the pdf as you are reading the article.
- IMPORTANT: do not use ChatGPT or any other LLM.

Examples

Below are a few sample excerpts– our ratings, rationale and the key sentences that led us to the rating.

Example 1

Mr. Enni said that many seemed convinced that the Reagan Administration's projected tax cuts would stimulate the economy and that interest rates would decline. He said they believed that inflation was now under control.

Rating: Low (Inflation is perceived to be under control)

Example 2

Bonds rose for a second day, as investors bet that economic reports this week will point to subdued inflation and slowing growth

Rating: Low (Investors think inflation is subdued)

Example 3

Britain's annual rate of inflation continued to fall in March, reaching the equivalent of 10.4 percent - the lowest level in three years, the Government announced Friday.Inflation in February was at the equivalent of 11 percent on an annual basis.

Rating: Low to medium (Continued downward path of inflation suggesting there is a steady trend. Yet, inflation is at 11 percent signaling that we have not reached a stable level).

Example 4

The Federal Reserve is almost certain to leave interest rates unchanged when its policy-making committee meets on Tuesday, but the central bank remains wary of resurgent inflation because of the economy's continued strength, analysts say. With overall price increases negligible and growth appearing to slow a bit from the blistering pace at the end of 1998, the Fed has no rationale for an immediate rate increase, economists say.

Rating: Low to medium. Low: Price increases are negligible and the Fed leaves interest rates unchanged. Medium: resurgent inflation, continued economic strength

Example 5

Concerns about the persistence of inflation below the Fed's 2 percent annual target appear to have diminished somewhat. The April account said that for many Fed officials, ''recent developments provided greater confidence that inflation would rise to 2 percent over the medium term.'' Other familiar concerns remained, in particular about the impact of renewed global weakness.

Rating: Low to medium (Inflation seems to be fairly stable and close to the target, some uncertainty regarding economic outlook).

Example 6

The number of adults participating in the labor force fell last month, suggesting Omicron may have added to hiring difficulties. And average hourly earnings continued to rise - good news for workers, but a possible source of concern for policymakers at the Federal Reserve, who have become increasingly worried that wage gains may become a larger driver of inflation.

Rating: Medium (Some uncertainty about labor market participation and wages, potentially driving inflation uncertainty)

Example 7

Sanctions could also spread economic instability worldwide by raising prices for key commodities that Russia produces "including oil, gas, fertilizer and palladium" and spur inflation in countries that import those products, landing a fresh blow just as the world emerges from the pandemic

Rating: Medium (Risk of potential sanctions creates uncertainty about the prices of commodities).

Exampe 8

The automotive retailer said tight demand and limited supply, driven by shortages in computer chips, is likely to continue well into the year. The tight supplies of new and used cars that have damped auto sales and pushed prices higher have not eased and are likely to linger well into this year, according to AutoNation, the country's largest automotive retailer.

Rating: Medium to high (Several uncertainties regarding the supply of chips and cars. Both are important in the overall economic context).

Exampe 9

Making matters worse, deflation has set in. Wholesale prices have been falling for years and now consumer prices appear to be falling. By creating the expectation that prices will continue to fall, deflation gives consumers and companies perverse incentives to postpone purchases. That can set off a downward spiral of falling spending, production, income and jobs

Rating: Medium to high (Risk of deflation. We would not rate it as high since they have been falling for years, suggesting some stability).

Exampe 10

Energy markets swung wildly, and shares in Moscow collapsed. Oil prices and global stock markets swung wildly on Thursday after Russia launched an invasion of Ukraine, raising fears of a wider economic crisis that could follow. [...] At one point, the price of oil jumped past $105 a barrel and European natural gas futures soared more than 50 percent, but energy prices fell after President Biden said the United States and other nations were considering a combined release of oil from strategic reserves.'

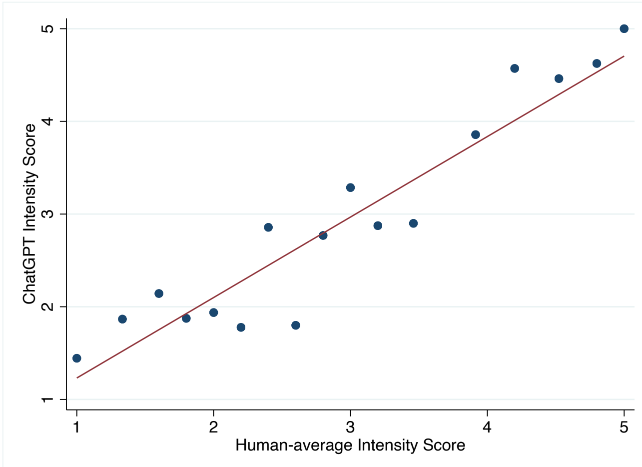
Rating: High (Extreme uncertainty about oil prices, a crucial input and component of inflation, as well as concerns about an economic crisis).

Exampe 11

The eurozone started 2022 much as it ended the previous year, with record-setting inflation that defied expectations. Now economists are wondering if the persistently high prices could pressure the European Central Bank to change its position that the situation is temporary.

Rating: High (Inflation is at a record level and has deviated significantly from expectations, suggesting there is high uncertainty for forecasters).

Figure B.7: **Human Audit: Comparison of Intensity Scores**



Note: This figure shows a binscatter of the LLM-based inflation uncertainty intensity score against the average intensity score assigned by human auditors. The sample consists of 155 articles included in the human audit.

Figure B.8: **LLM vs Human Scores**

LLM-Intensity Score: 30. Human scores: 1/1/1/1/1

THE MARKETS: BONDS;Yields at 3-Week Lows, With Favorable Inflation News Seen, 1999-03-16:
Treasury bond prices rose for a second day, pushing yields to the lowest in almost three weeks, as investors bet that economic reports this week will point to subdued inflation and slowing growth."The market's going to see some good news," in the reports this week, said Alan Day, who helps manage $4 billion at Stratevest Group in Burlington, Vt. "There's no threat of rising rates of inflation." The price of the 30-year Treasury bond fell 2/32 , to 96 1/32 . The bond's yield, which moves in the opposite direction from the price, rose to 5.52 percent, from 5.51 percent Friday.Trading volume was the lightest this year, according to GovPX Inc., a bond pricing service.Traders and investors will be paying close attention to February figures on industrial output, due today, and consumer prices, the most widely watched measure of inflation, to be released Thursday. Economists expect production to be unchanged and prices to rise just one-tenth of 1 percent."After weeks of relentlessly strong data, we have the prospect of some softer economic reports," said Dana Johnson, the head of research at First Chicago Capital Markets Inc. [...]

LLM-Intensity Score: 80. Human scores: 5/5/4/5/5

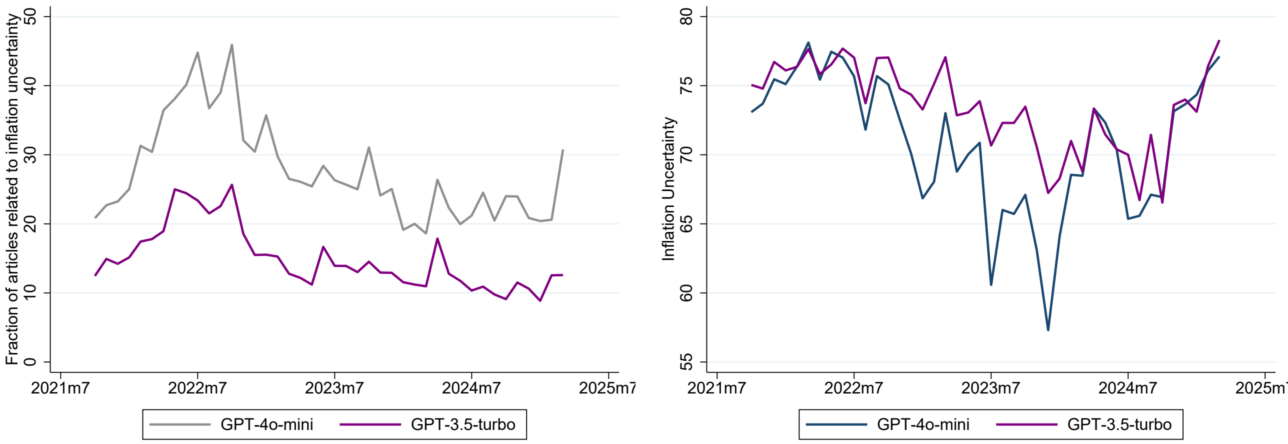
Oil prices climb as Ukraine crisis deepens, 2022-02-27:
A nuclear threat, and skepticism at potential talks. A nuclear threat, and skepticism at potential talks.Oil prices jumped Sunday night, as President Vladimir V. Putin's saber-rattling order to put his country's nuclear forces on high alert overshadowed hopes for negotiations between Russia and Ukraine.The announcement by President Volodymyr Zelensky that a Ukrainian delegation would meet with a Russian delegation near the Ukraine-Belarus border for talks without preconditions was viewed skeptically by oil traders and most political analysts and Western officials.Traders had not driven up prices in recent days because Western sanctions against Russia have so far not impeded the export of oil and natural gas to Western Europe. But the Brent oil benchmark soared by more than 5 percent on Sunday to $103 a barrel while the American West Texas Intermediate benchmark climbed even higher, by almost 6 percent, to $97 a barrel.American gasoline prices have risen about a penny a gallon every day over the last week, according to surveys by the AAA motor club. At $3.60 a gallon for regular gasoline, the national average is nearly a dollar higher than it was a year ago.Risks of rising energy prices remain high as the Russians press on with their invasion of Ukraine. In the early days, the Russian offensive bogged down in the face of strong resistance from the Ukrainian armed forces and Ukrainian citizens.Bombing and rockets could damage vital pipelines that run through Ukraine, though that has not happened yet. Some Republican leaders and members of Congress of both parties are pressing for tougher sanctions on energy transactions. Western oil companies may decide that doing business with Russia is not worth the risks, especially if Western technology and oil services are either hit with sanctions or because financial sanctions will impede Russian payments. Perhaps the greatest uncertainty will be the Russian response, according to a report released by RBC Capital Markets on Sunday. The central bank sanctions will sharply reduce Russia's access to its foreign exchange reserve war chest and proceeds from oil sales in overseas accounts. The West's tough economic stance against Russia is already having an effect. BP said on Sunday that it would exit its nearly 20 percent stake in Rosneft, the giant Russian company, and that it would remove its two representatives from the Rosneft board. It was a climactic retreat from the British-based company after three decades of doing business in Russia.Ukraine's gas pipeline operators said on Sunday that natural gas transmission that goes through the country to much of the rest of Europe was normal.Another wild card will be Russia's stance at a meeting on Wednesday of OPEC Plus, in which it is a partner with Saudi Arabia and other major producers. The group is meeting to discuss how much to increase production levels to ease global price increases. Washington so far has had little success in pressing the group to raise production.

B.4 Testing for Look-ahead Bias

Figure B.9: **Comparison: ChatGPT-4o-mini vs. ChatGPT-3.5-turbo**

(A) Fraction of articles related to inflation uncertainty (Q1)

(B) Average monthly intensity score (Q2)



Note: This figure shows inflation uncertainty identified from an analysis of New York Times articles using ChatGPT. The left panel shows the monthly fraction of business-related articles flagged by the LLM as pertaining directly to inflation uncertainty. The right panel shows the average inflation uncertainty intensity score assigned by the LLM (on a scale from 1-100) to articles in a given month.

C Information about Inflation Surveys

Survey of Consumer Expectations (SCE). The Survey of Consumer Expectations (SCE) conducted by the Federal Reserve Bank of New York since 2013 is a nationally representative, internet-based survey of a rotating panel of approximately 1,300 household heads. We use the variable *inflation uncertainty* as 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 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, survey respondents are also asked for outcome probabilities for "inflation three-years ahead (over the twelve-month period between [current date + 2 years] and [current date + 3 years])". The data are available between June 2013 and March 2025.

Survey of Professional Forecasters (SPF). The Survey of Professional Forecasters (SPF) is conducted by the Federal Reserve Bank of Philadelphia on a quarterly basis, typically at the beginning of the second month of the quarter, and surveys a wide range of professional forecasters. Alongside other questions, the SPF also asks survey participants 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 or core PCE inflation "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 compute the mean probability across all survey respondents for an inflation outcome and then compute the standard deviation. The data is available between the first quarter of 2007 and the first quarter of 2025.

Michigan. The University of Michigan Survey of Consumers is a rotating panel survey that captures consumer attitudes and expectations regarding the U.S. economy. It provides monthly data on consumer sentiment, including year-ahead and five-year-ahead inflation expectations, derived from a nationally representative sample.

Blue Chip. The Blue Chip Economic Indicators survey is a monthly survey of leading business economists that provides consensus forecasts for key macroeconomic variables in the United States. Survey participants submit point forecasts for variables such as GDP growth, inflation, and interest rates.

Greenbook. The Greenbook comprises internal economic forecasts prepared by the Federal Reserve Board's staff prior to each Federal Open Market Committee (FOMC) meeting. These documents include detailed projections on variables such as GDP, inflation, and unemployment, based on current economic data and policy assumptions. While initially confidential, Greenbook forecasts are released to the public with a five-year lag.

Summary of Economic Projections (SEP). The Summary of Economic Projections (SEP) is released by the Federal Reserve following every other Federal Open Market Committee (FOMC) meeting—typically four times per year. It reflects the individual forecasts of all FOMC participants, including both voting and non-voting members of the Board of Governors and regional Federal Reserve Bank presidents. The

SEP includes projections for key macroeconomic variables such as real GDP growth, the unemployment rate, personal consumption expenditures (PCE) inflation, and the appropriate path of the federal funds rate (the "dot plot") over the current year, the next few years, and the longer run. Projections are reported as ranges and central tendencies across participants. The SEP does not represent a consensus forecast or policy commitment but provides a window into the range of views among policymakers about the economic outlook and appropriate monetary policy.

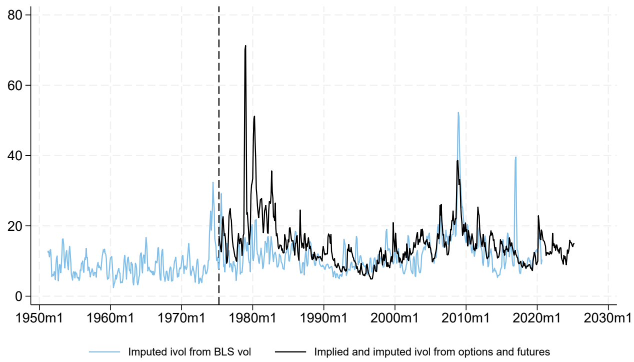
D Historical Extension – Additional Information

Table D.3: Availability of Commodity Options and Futures

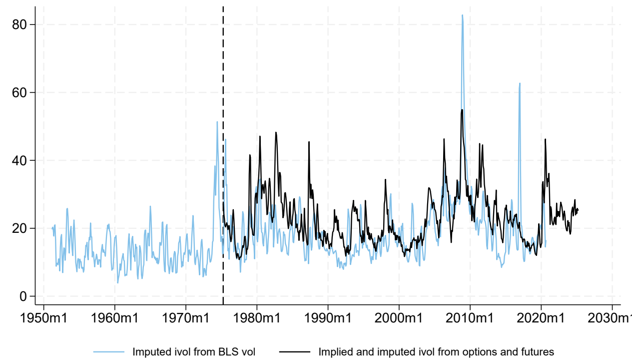
	Start of Options	Start of Futures	Sources for Earlier Dates
Gold	1982m11	1975m4	The BLS Metals Index from 1951 until earliest futures date, gold firms' (SIC 1041) stock returns prior to 1951
Silver	1984m10	1975m4	The BLS Metals Index from 1951 until the earliest futures date, gold firms' (SIC 1041) stock returns prior to 1951
Soybean	1984m10	1959m9	BLS Food Index from 1951 until 1959, the PPI Agriculture Index prior to 1951
Corn	1985m2	1959m9	BLS Food Index from 1951 until 1959, the PPI Agriculture Index prior to 1951
Oil	1986m12	1983m6	Oil firms' (SIC 1311) stock returns prior to earliest futures date
Natural Gas	1992m11	1990m7	Oil firms' (SIC 1311) stock returns prior to earliest futures date

D.1 Imputed Commodity Volatility from 1951-Current

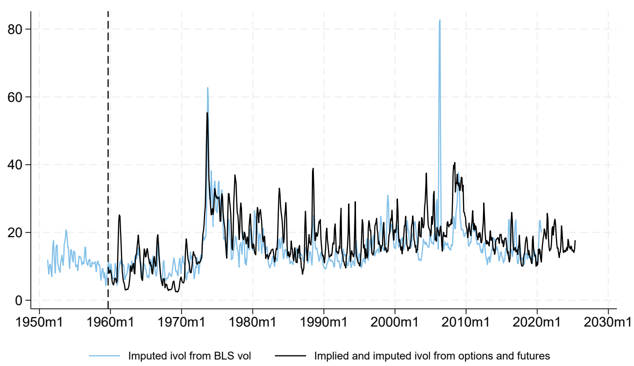
(C) Gold



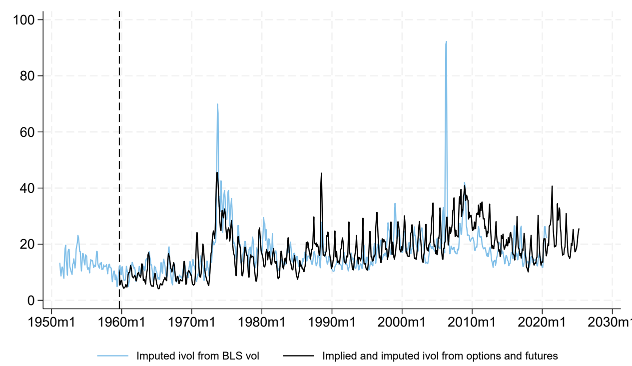
(D) Silver



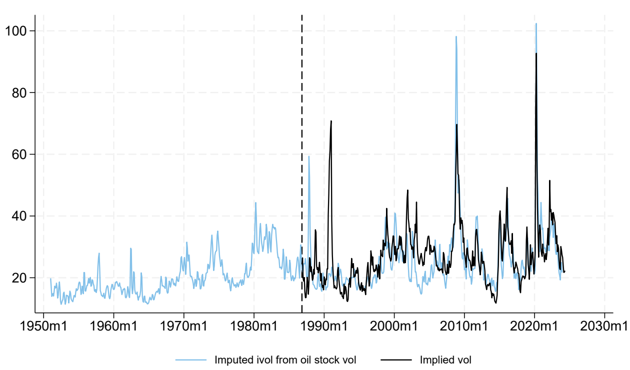
(E) Soybean



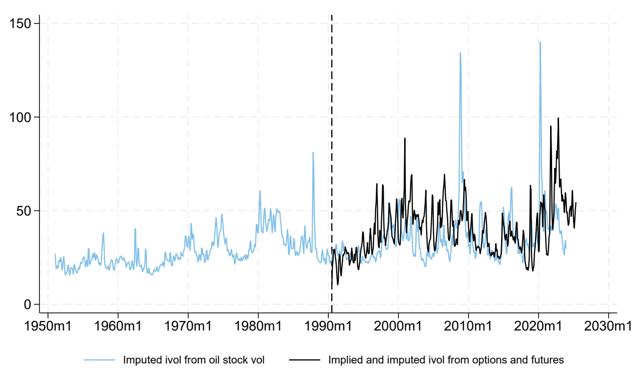
(F) Corn



(G) Oil

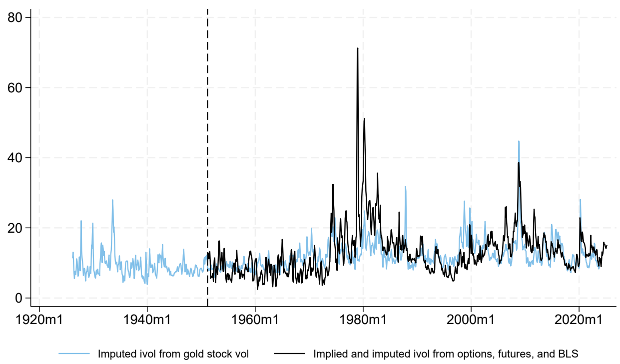


(H) Natural Gas

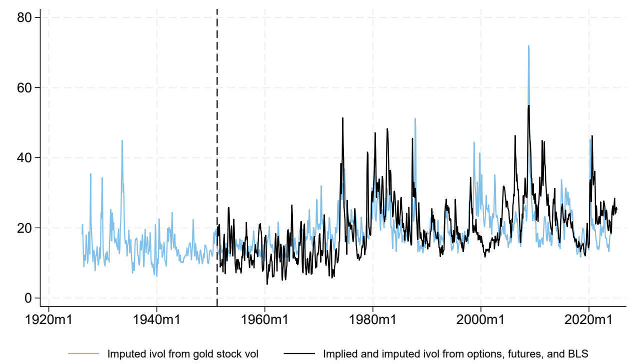


D.2 Imputed Commodity Volatility from 1926-Current

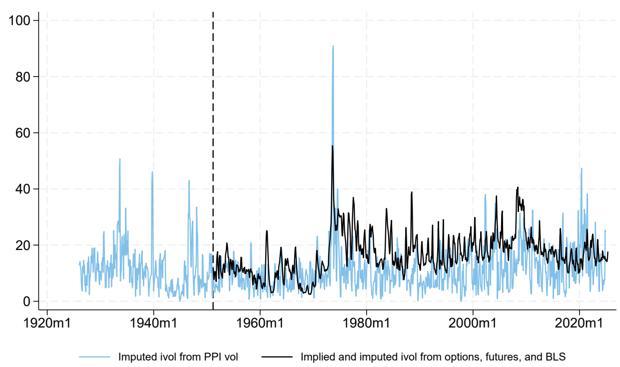
(A) Gold



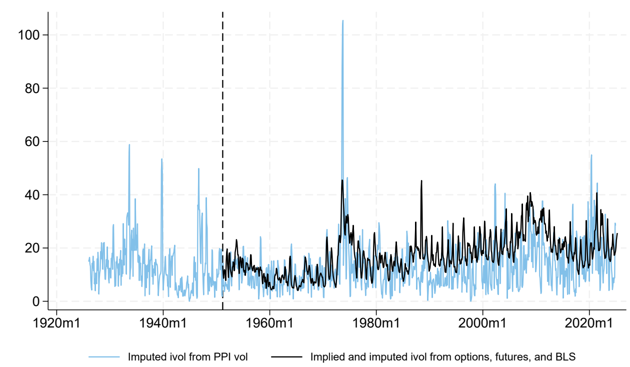
(B) Silver



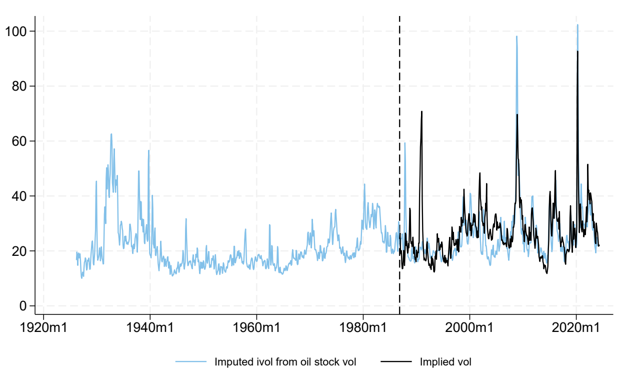
(C) Soybean



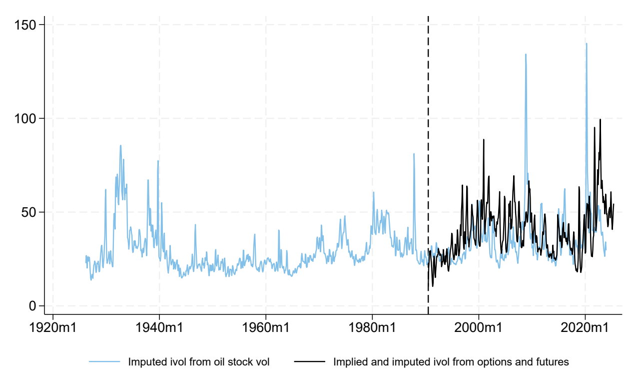
(D) Corn



(E) Oil

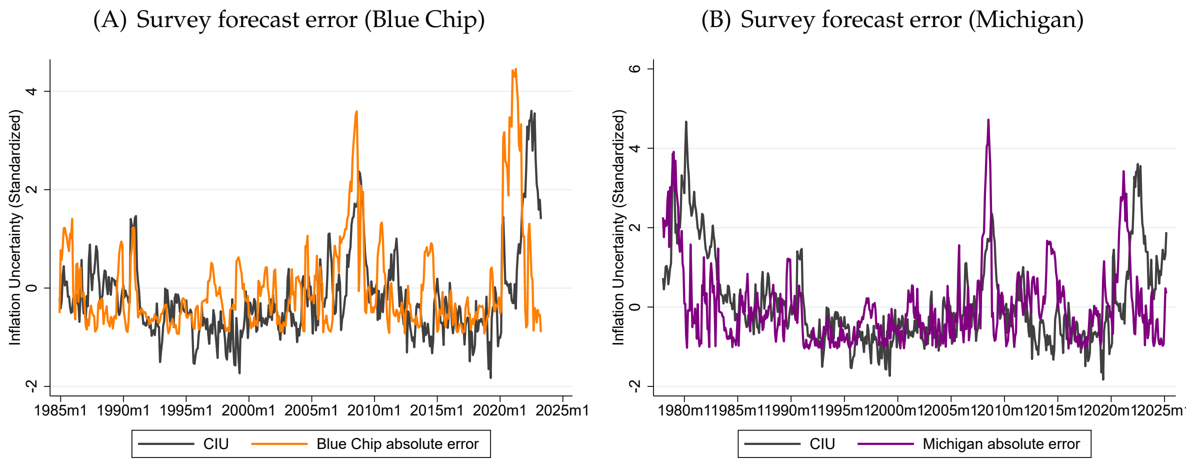


(F) Natural Gas



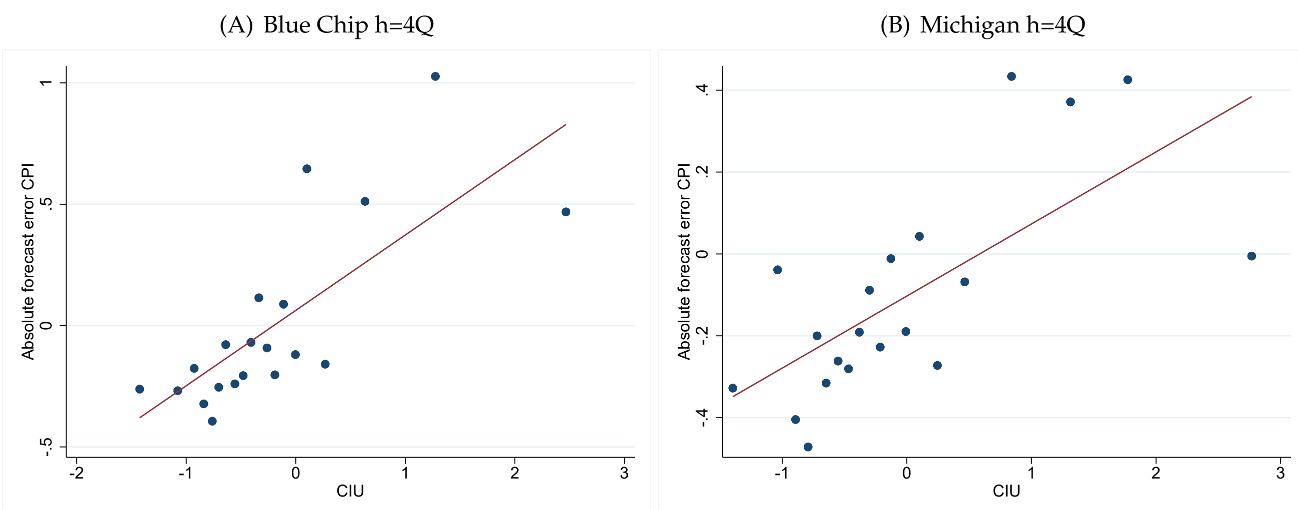
E Inflation Uncertainty and Survey Forecast Errors

Figure E.10: **Comparison with Forecast Errors and Disagreement**



Note: This figure compares CIU to absolute survey forecast errors defined as the difference between the consensus forecast and realized inflation. The availability of the series is described in the note of Table 6.

Figure E.11: **Inflation Uncertainty vs. Absolute Forecast Errors**

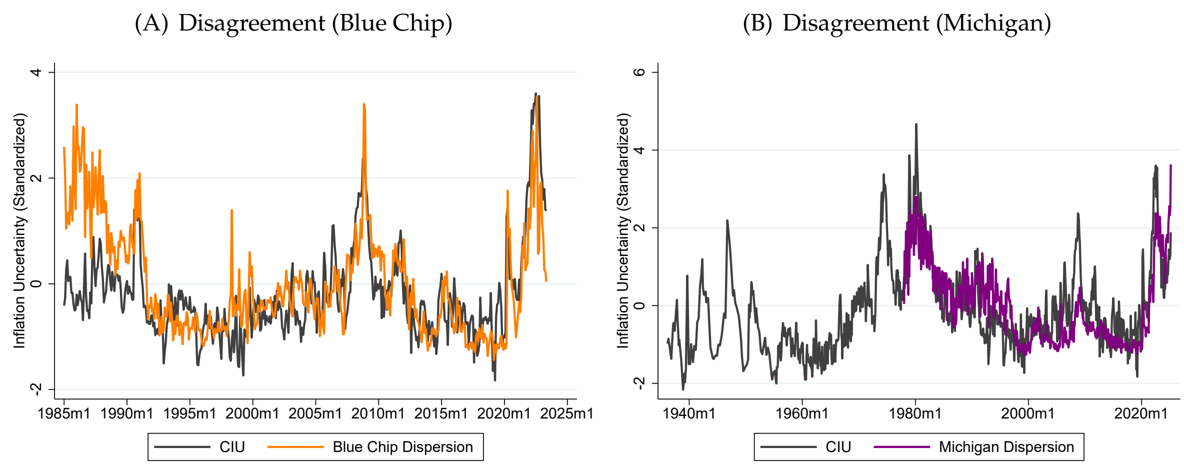


Note: This figure shows a binscatter of (standardized) absolute inflation forecast errors and inflation uncertainty as measured by CIU. Panel (A) uses Blue Chip forecasts for year-over-year (YoY) inflation in one year. Panel (B) uses Michigan forecasts for year-over-year (YoY) inflation.

F Inflation Uncertainty and Disagreement about Inflation

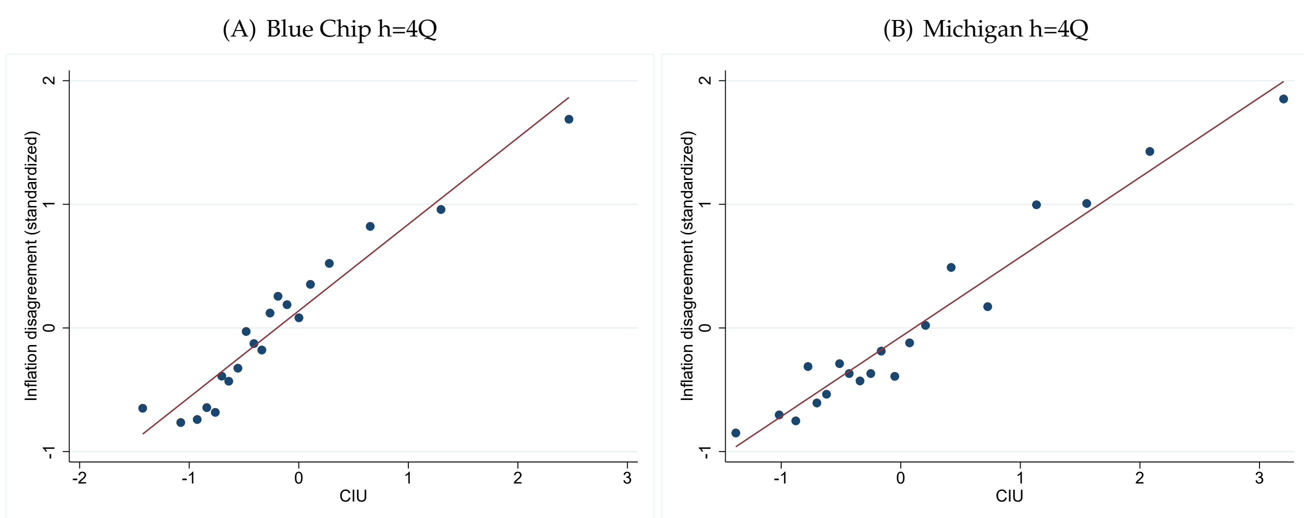
F.1 Empirical Relationship

Figure F.12: **Comparison with Inflation Disagreement**



Note: This figure compares CIU to inflation forecast errors and inflation disagreement measured as the dispersion among survey respondents for the inflation level forecast. The availability of the series is described in the note of Table 6.

Figure F.13: **Inflation Uncertainty and Inflation Disagreement**



Note: This figure shows binscatter of (standardized) inflation disagreement/dispersion and inflation uncertainty as measured by CIU. Panel (A) uses Blue Chip forecasts for year-over-year (YoY) inflation in one year. Panel (B) uses Michigan forecasts for year-over-year (YoY) inflation.

F.2 Theoretical Relationship

This appendix uses a simple linear-Gaussian setting with dispersed information about inflation to highlight the relationship between uncertainty and disagreement (or equivalently, belief dispersion). Consider an economy where a continuum of agents (indexed by i) have identical priors over inflation

$\pi_t \sim \mathcal{N}(0, \sigma_\pi^2)$. Agent i receives a private signal:

$$s_{it} = \pi_t + e_{it} \qquad e_{it} \sim \mathcal{N}(0, \sigma_{e,t}^2) \tag{F.14}$$

This heterogeneity in information could stem, for example, from differences in models and/or data sources. From Bayes' rule, posterior beliefs are given by

$$\pi_t | s_{it} \sim \mathcal{N}(\mu_i, \text{Uncert}_t) \qquad \text{where} \tag{F.15}$$

$$\mu_{it} \equiv \frac{\sigma_{\pi,t}^2}{\sigma_{\pi,t}^2 + \sigma_{e,t}^2} s_{it} \qquad \text{and} \tag{F.16}$$

$$\text{Uncert}_t \equiv \frac{\sigma_{\pi,t}^2 \sigma_{e,t}^2}{\sigma_{\pi,t}^2 + \sigma_{e,t}^2} \tag{F.17}$$

are the posterior mean and variance respectively. Note that the posterior variance, Uncert_t is increasing in the signal noise, $\sigma_{e,t}^2$. Disagreement is defined as the cross-sectional dispersion in the posterior mean μ_i:

$$\text{Disp}_t \equiv Var(\mu_{it}) = \sigma_{e,t}^2 \left(\frac{\sigma_{\pi,t}^2}{\sigma_{\pi,t}^2 + \sigma_{e,t}^2} \right)^2 \tag{F.18}$$

Equation (F.18) highlights the two forces of higher signal noise, $\sigma_{e,t}^2$, on disagreement: on the one hand, higher $\sigma_{e,t}^2$ leads to more dispersed signals, but on the other, it induces agents to place a lower weight on their private signals, a force which reduces dispersion. As a result, the overall effect is ambiguous. It is straightforward to show that dispersion increases (decreases) with signal noise at low (high) levels of σ_e^2. Thus, uncertainty unambiguously increases with noisier private signals but dispersion is non-monotonic. Higher prior uncertainty ($\sigma_{\pi,t}^2$), in contrast, raises both uncertainty and dispersion. Thus, the link between disagreement and uncertainty is a complicated one: a positive relationship obtains when private signals are relatively precise or when fundamental uncertainty changes. Our results suggest that this is the empirically relevant region in our sample.

G Robustness: Inflation Uncertainty and Asset Prices

It is often argued that the post-Volcker era constituted a different monetary policy regime in the US. This subsection explores the robustness of our insights in Section 4 by repeating the analysis on the post-1980s sample. Table G.4 presents the results. The broad patterns are similar to Table 7, though there are some notable differences. Panel (A) shows that the effect of uncertainty on real assets (gold, silver and housing) in the post-1980s era is comparable to those estimated over the longer sample. However, the effect on nominal bond valuations is no longer statistically significant. In other words, in the more recent sample, more uncertain inflation does not seem to make investors more nervous about holding long-term nominal claims. The reasons behind this shift are not obvious. One possible explanation is a change in the nature of the marginal investor in the long term bond market, such as a shift towards investors for whom the risk may be less salient or relevant (e.g. foreign central banks, the Federal Reserve). It could also reflect changes in the joint distribution of inflationary shocks and interest rates. For example, the restoration of the Fed's inflation-fighting credibility in the post-Volcker era meant that long-term inflation expectations were likely to stay anchored even in the face of inflationary shocks. This would tend to make holding long-term bonds less risky. Of course, this argument doesn't explain the lack of an inflation risk premium. That would require investors to believe that changes in real rates offset the negative effects of future inflation.[1]

The estimates in Panel (B) show the effects on valuations of claims on business assets, i.e. on equities and corporate bonds. The results are broadly in line with the longer sample: if anything, equity yields and corporate bond spreads tend to rise more sharply with inflation uncertainty post-1980. The one difference is related to the findings on long term nominal rates in Panel (A) – corporate bond *yields* do not show a statistically significant response to CIU.

[1] How might such a scenario unfold? Consider a transitory adverse supply shock. The Fed, sufficiently emboldened by well-anchored inflation expectations, might decide to *cut* interest rates to offset the negative effects on the labor market.

Table G.4: **Inflation Uncertainty and Asset Prices, 1980–2025**

(A) Nominal vs. real assets

	log(1/Real Gold Price)		log(1/Real Silver Price)		log(1/Real House Prices)		Long-term risk-free rate	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Composite Inflation Uncertainty (CIU)	-0.306***	-0.309***	-0.291***	-0.341***	-0.121**	-0.116**	-0.701	-0.255
	(-3.95)	(-4.61)	(-3.78)	(-4.50)	(-2.44)	(-2.43)	(-1.32)	(-0.50)
Observations	538	538	538	538	538	538	538	538
R^2	0.236	0.450	0.227	0.339	0.175	0.265	0.314	0.404
CPI YoY	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Uncertainty Controls		Yes		Yes		Yes		Yes
Sample Start	1980m6	1980m6	1980m6	1980m6	1980m6	1980m6	1980m6	1980m6
Sample End	2025m3	2025m3	2025m3	2025m3	2025m3	2025m3	2025m3	2025m3

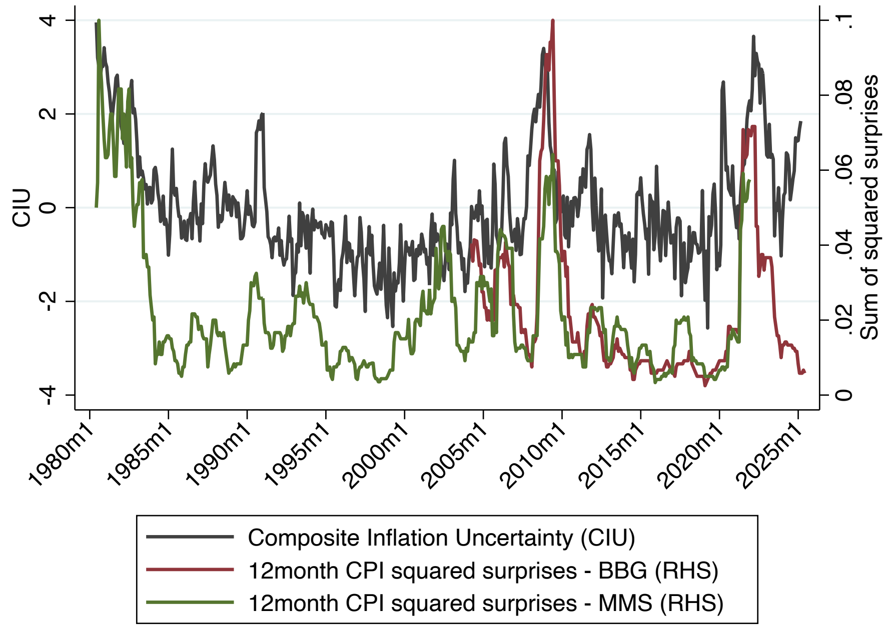
(B) Claims on business assets

	log(Earnings/Stock prices)			Corporate bond spread		Corporate bond yield	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Composite Inflation Uncertainty (CIU)	0.0491	0.0864	0.0823	0.297**	0.278***	-0.399	0.0205
	(0.64)	(1.05)	(0.68)	(2.37)	(2.59)	(-0.63)	(0.04)
Observations	535	535	535	538	538	538	538
R^2	0.213	0.239	0.248	0.299	0.349	0.293	0.384
CPI YoY	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Uncertainty Controls		Yes	Yes		Yes		Yes
Sample Start	1980m6	1980m6	1980m6	1980m6	1980m6	1980m6	1980m6
Sample End	2024m12	2024m12	2024m12	2025m3	2025m3	2025m3	2025m3

Note: This table shows regressions of asset price valuations on inflation uncertainty. The dependent variables in Panel (A) are: (i) the spot gold price obtained from GlobalFinancialData scaled by the CPI index, (ii) the spot spot price obtained from GlobalFinancialData scaled by the CPI index, (iii) the real home price index from Robert Shiller's website, (iv) the yield on Moody's AAA-rated corporate bonds. The dependent variables in Panel (B) are: (i) the S&P 500 index to earnings where earnings are the three-year average of annual S&P 500 earnings before special items following Hillenbrand and McCarthy (2024), (ii) the yield difference between Moody's BAA-rated and AAA-rated corporate bonds, (iii) the yield on Moody's BAA-rated corporate bonds. All-equity financed firms are firms whose average quasi-market leverage is below 10% (leverage is computed as the ratio of long-term book debt to market equity plus long-term book debt). All regressions control for the level of inflation (CPI YoY). Controls for uncertainty are the EPU and the VIX. When VIX is not available, we impute the VIX with past 3-month realized volatility of stock market returns. t-stats based on Newey-West standard errors are reported in parentheses. Significance levels: *(p<0.10), **(p<0.05), ***(p<0.01).

H Inflation Uncertainty and CPI Announcement Surprises

Figure H.14: **Inflation Uncertainty and CPI Announcement Surprises**



Note: This figure plots Composite Inflation Uncertainty and the sum of squared CPI announcement surprises, $\overline{\text{Surprise}_t^2}$, as defined in (12). The surprises are computed using forecasts from Money Market Services (MMS) for the period February 1980 to December 2004 as well as from Bloomberg (BBG) for the period January 2005 through March 2025.

I Local Projection with CIU innovation

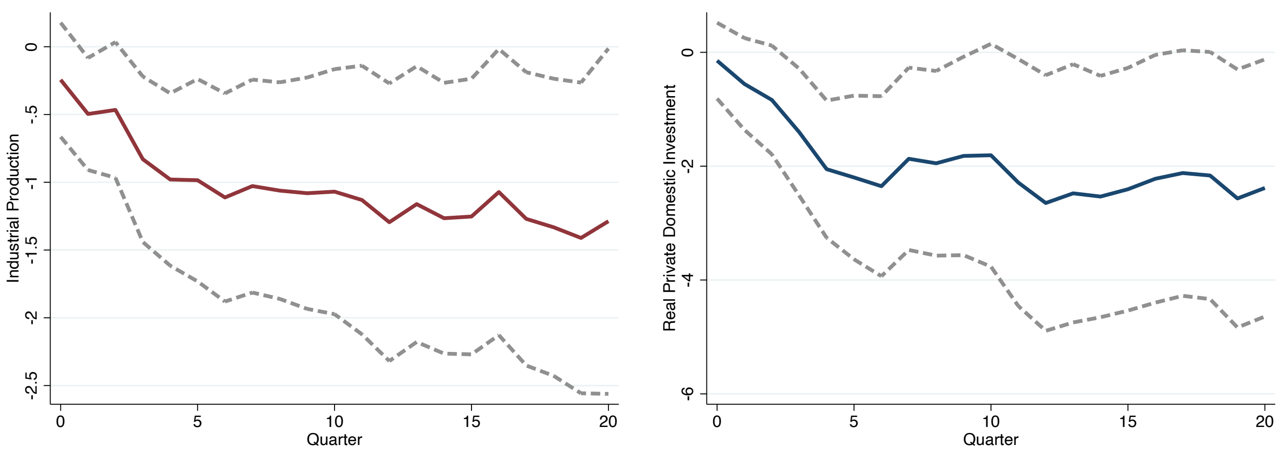
Here, we repeat our local projection analysis from Section 4 and Figure 9 treating the change in CIU as the shock of interest (instead of the squared announcement surprise). This is in the spirit of the ordering assumption in the VAR analysis in Section 4 where innovations to CIU were assumed to be contemporaneously unaffected by the other variables. Formally, we estimate the following specification:

$$y_{t-1,t+h} = \beta_0 + \beta_1 \cdot \Delta CIU_t + \epsilon_{t,h} \tag{I.19}$$

where $\Delta CIU_t = CIU_t - CIU_{t-1}$. The patterns are very similar to Figure 9, but with higher magnitudes: investment declines by about 2 pp and output by 1 pp, with both impulse responses showing considerable persistence. Both forms of investment – residential and business – show significant declines with markedly larger effects for housing.

Figure I.15: **Local projection: Response of investment & production to inflation uncertainty shock**

(A) Industrial production response to CIU innovation (B) Investment response to CIU innovation



Note: This figure shows the impulse responses of industrial production (Panel A) and investment (Panel B) to inflation uncertainty shocks. The local projection method uses (standardized) CIU innovation as the shock variable. The local projection is estimated using quarterly data from 1980Q1 to 2025Q1. The gray lines show 90 percent confidence bands.

J Text-based Demand, Supply, and Policy Factor Analysis II

In this subsection, we describe an alternative approach to uncovering the driving forces behind inflation uncertainty. In order to assess the roles of uncertainty about consumer demand, firms' input costs (supply), and policy uncertainty, we construct time series for these different forms of uncertainty, following the same procedure as with our news-based measure. Specifically, we ask ChatGPT to flag articles from the NY Times related to uncertainty about consumer demand, supply, trade policy and fiscal policy. We follow the same approach as in the construction of NIU when constructing the corresponding textual factors. More details on the ChatGPT prompt and the time series of the textual factors are provided in Figure J.16 and J.17.

We then estimate a time-series regression where we relate inflation uncertainty to the underlying uncertainty drivers in Table J.5. Column (1) reports the estimated coefficients from regressing CIU, our Composite Inflation Incertainty measure on the series for uncertainty about consumer demand and supply. It shows evidence of a strong positive link between inflation uncertainty and uncertainty over supply-related factors – a one-standard-deviation rise in the latter is associated with CIU being 0.63 standard deviations higher. In contrast, uncertainty about demand conditions has a positive but much more muted relationship. Columns (2)-(3) demonstrate that this pattern is robust to adding policy uncertainty. While general economic policy uncertainty does not exhibit a significant relationship with inflation uncertainty controlling for demand and supply uncertainty, fiscal policy-related concerns seem to influence inflation uncertainty. By contrast, trade policy has historically not played a significant role. These relationships persist even after controlling for the level of inflation, though they weaken somewhat – suggesting that periods of high inflation uncertainty often coincide with elevated inflation.

A potential issue with interpreting these estimates is that movements in CIU might be partly picking up changes in risk premia, rather than uncertainty. To address this concern, columns (4)-(6) repeat the analysis with our news-based measure, NIU, which is arguably less affected by risk premia. The estimated coefficients are quite similar in both sign and magnitude, suggesting that the patterns are indeed related to uncertainty.

Panel B of Table J.5 adds commonly used proxies for demand and supply conditions, namely the Consumer Sentiment Index from the University of Michigan Survey and the Global Supply Chain Index. These variables do not directly measure uncertainty – rather, they are intended to capture first-moment changes in demand and supply conditions. Even so, column (3) shows that they also have significant effects on inflation uncertainty. The signs are intuitive: high uncertainty is associated with poor consumer sentiment (when the Michigan index is low) and increased pressure on supply chains. The attenuation in the estimated coefficients on the demand and supply uncertainty series is consistent with this intuition as well.

Figure J.18 depicts the contributions of each factor over time from 1980 through 2025.[2] In line with the table, it shows the important role played by supply-related factors: their relative stability helped keep inflation uncertainty low during the 1990s and 2000s, but contributed significantly to the run-up in uncertainty in the aftermath of the COVID-19 pandemic.

[2]Formally, the figure plots the product of the variables of interest (normalized) and the estimated coefficient from regressing them on CIU.

Figure J.16: **Textual Factors: ChatGPT Prompts**

(A) Consumer demand uncertainty

Read the following news article: {article}

Q1: Is the article directly related to uncertainty about consumer demand?

Consumer demand reflects the willingness and ability of households to purchase goods and services, is shaped by consumer confidence and sentiment, and often measured by retail activity.

Q2: If your answer to Q1 is yes, how stable/uncertain is consumer demand 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. Temperature: 0.0.

(B) Supply uncertainty

Read the following news article: {article}

Q1: Is the article directly related to uncertainty about firms' input costs?

Input costs include energy and raw material costs, supply chain challenges, and other factors affecting the costs of production and operation. Do not consider labor costs or wages as input costs.

Q2: If your answer to Q1 is yes, how stable/uncertain are firms' input costs 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. Temperature: 0.0.

(C) Fiscal policy uncertainty

Read the following news article: {article}

Q1: Is the article directly related to uncertainty about fiscal policy?

Fiscal policy is about government budget deficits, taxes, government spending, and debt sustainability.

Q2: If your answer to Q1 is yes, how stable/uncertain is fiscal policy 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. Temperature: 0.0.

(D) Trade policy uncertainty

Read the following news article: {article}

Q1: Is the article directly related to uncertainty about trade policy?

Trade policy is about import tariffs, trade barriers, and trade agreements.

Q2: If your answer to Q1 is yes, how stable/uncertain is trade policy 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. Temperature: 0.0.

Table J.5: **The Determinants of Inflation Uncertainty**

Panel A: Uncertainty Measures

	CIU			NIU		
	(1)	(2)	(3)	(4)	(5)	(6)
Consumer demand uncertainty	0.190*	0.190	0.074	0.137**	0.137**	0.029
	(1.81)	(1.23)	(0.67)	(2.13)	(2.55)	(0.42)
Supply uncertainty	0.633***	0.636***	0.444***	0.587***	0.591***	0.442***
	(6.85)	(5.60)	(7.49)	(6.80)	(9.21)	(7.62)
Economic Policy Uncertainty (EPU)		-0.007			-0.010	
		(-0.05)			(-0.13)	
Trade policy uncertainty			0.033			0.109*
			(0.53)			(1.91)
Fiscal policy uncertainty			0.135***			0.196***
			(2.72)			(4.31)
CPI yoy			0.585***			0.318***
			(5.30)			(4.37)
Observations	538	538	538	538	538	538
R^2	0.384	0.384	0.558	0.438	0.438	0.551

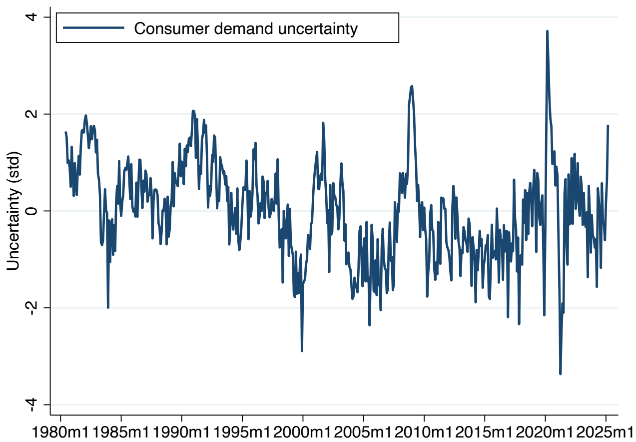
Panel B: Demand & Supply

	CIU			NIU		
	(1)	(2)	(3)	(4)	(5)	(6)
Consumer demand uncertainty	0.190*	0.076	0.112	0.137**	0.074	0.006
	(1.81)	(0.70)	(1.32)	(2.13)	(1.34)	(0.12)
Supply uncertainty	0.633***	0.403***	0.269***	0.587***	0.460***	0.380***
	(6.85)	(5.26)	(4.81)	(6.80)	(8.26)	(9.26)
Consumer sentiment (Michigan)		-0.646***	-0.633***		-0.356***	-0.454***
		(-6.40)	(-7.66)		(-5.03)	(-5.98)
Global Supply Chain Pressure Index			0.156**			0.109
			(2.31)			(1.60)
Observations	538	538	327	538	538	327
R^2	0.384	0.589	0.695	0.438	0.528	0.593

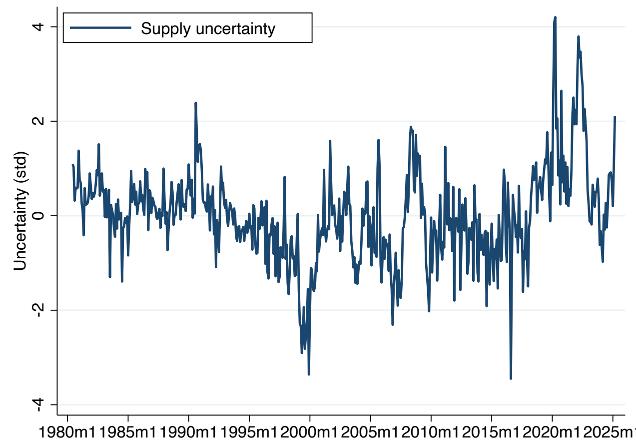
Note: This table shows contemporaneous regressions of inflation uncertainty on various explanatory variables. The consumer demand, supply, trade policy and fiscal policy uncertainty measures are extracted from NY Times articles following the same procedure as the construction of the NIU. Internet Appendix Section J provides more details. Economic Policy Uncertainty (EPU) is from Baker, Bloom, and Davis 2016. The Global Supply Pressure Chain Index is from the New York Fed website, https://www.newyorkfed.org/research/policy/gscpi is available since 1998. Significance levels: *(p<0.10), **(p<0.05), ***(p<0.01).

Figure J.17: **Time Series of Textual Factors**

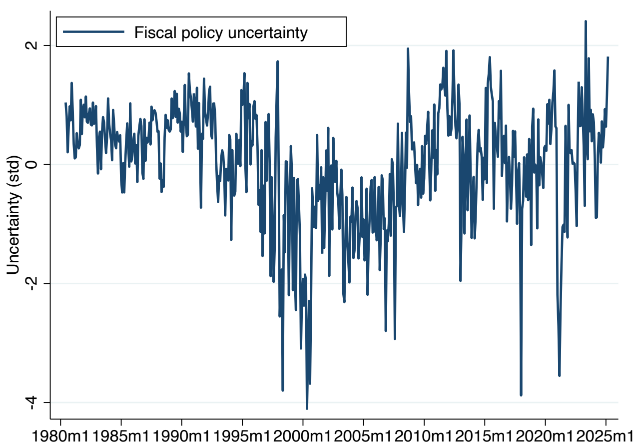
(A) Consumer demand uncertainty



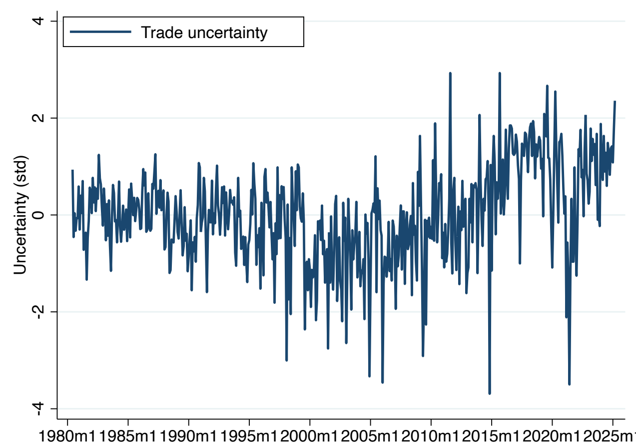
(B) Supply uncertainty



(C) Fiscal policy uncertainty

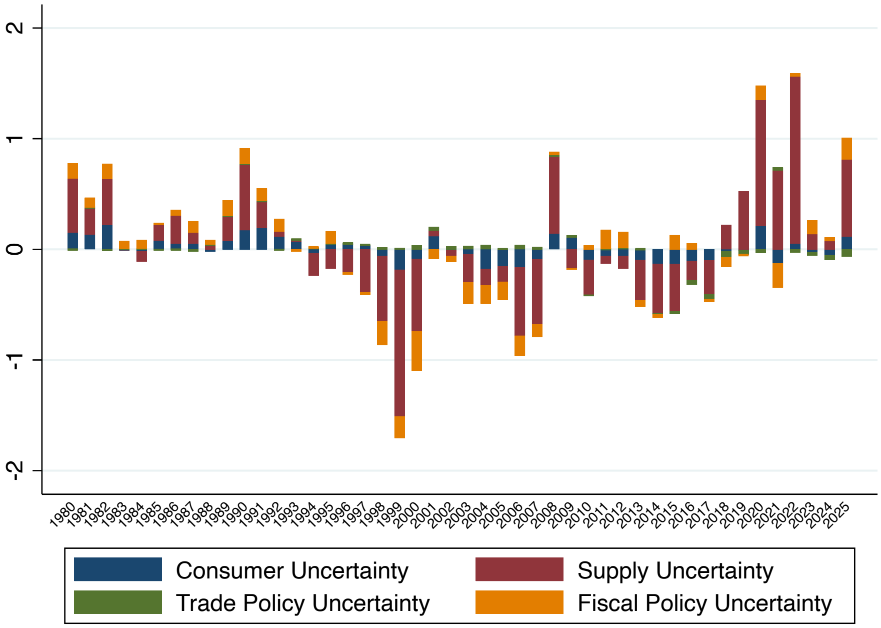


(D) Trade policy uncertainty



Note: This figure shows the time series of the textual factors of consumer demand uncertainty, supply uncertainty, fiscal policy uncertainty and trade policy uncertainty.

Figure J.18: **Decomposing Inflation Uncertainty**



Note: This figure shows the predicted value from a regression of inflation uncertainty on the textual uncertainty measures. The consumer demand, supply, trade policy and fiscal policy uncertainty measures are extracted from NY Times articles following the same procedure as the construction of the NIU. Internet Appendix Section J provides more details.