Inflation and Uncertainty: Evidence from GARCH-MIDAS-in-Mean Modelling*

Chaoyi Chen – Tamas Barko – Olivér Nagy

We revisit the relationship between inflation and inflation uncertainty using a novel GARCH-MIDAS-in-Mean approach, which allows for the decomposition of inflation uncertainty into short-term and time-varying long-term components. We test our model on UK data. Our findings indicate that macroeconomic and financial variables significantly influence the long-term component of inflation uncertainty. By enabling long-term uncertainty to vary over time through MIDAS filtering, we show that the evidence for past inflation raising short-run uncertainty weakens compared to results that assume a constant long-term inflation uncertainty component. However, our results support the Cukierman–Meltzer hypothesis, indicating that the impact of inflation uncertainty on inflation becomes more robust and pronounced when longer samples are used, although this effect is sensitive to structural breaks, such as the VAT cut and the Covid-19 pandemic. Additionally, we find no evidence that changes in inflation feed back into short-run uncertainty.

Journal of Economic Literature (JEL) codes: E31, E52, C22

Keywords: Inflation, Inflation uncertainty, GARCH-MIDAS models

1. Introduction

Understanding the relationship between inflation and inflation uncertainty is one of the most critical issues for monetary authorities, with debates surrounding both the effects of inflation on its own uncertainty and the reverse effect of inflation uncertainty on inflation rates (see, for example, *Greenspan 2004*).

* The papers in this issue contain the views of the authors which are not necessarily the same as the official views of the Magyar Nemzeti Bank.

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The authors would like to thank the participants of the AI Workshop at the MNB Institute for their valuable comments. We are also grateful to the editor and the two anonymous referees for their constructive feedback and thoughtful suggestions, which have substantially improved the quality and clarity of this paper. The views and opinions expressed herein are those of the authors and do not necessarily reflect those of their respective employers.

The first version of the English manuscript was received on 31 March 2025.

DOI: https://doi.org/10.33893/FER.24.3.52

The existing literature offers mixed evidence, highlighting the complexity of the inflation-uncertainty relationship. Notably, much of the literature relies on GARCH (-in-Mean) models, which inherently assume that long-term uncertainty remains constant over time, a restrictive and unintuitive assumption.[1] Our paper aims to relax this assumption. We contribute to the literature by applying a novel GARCH-MIDAS-in-Mean model, as formulated by *Engle et al.* (*2013*), to revisit the inflation-uncertainty nexus. Our modelling framework allows us to decompose inflation uncertainty into short-term and time-varying long-term components, assuming the long-term component driven by smoothed (longer-horizon) realised volatility or other macro-finance variables. This approach enables us to (1) assess the impact of inflation on short-run inflation uncertainty, which is often more critical given the smoother nature of long-term uncertainty, and (2) evaluate the influence of total inflation uncertainty – defined as the product of both time-varying short-run and long-run uncertainty components – on inflation itself.

We analyse an updated UK dataset extending through 2023 and compare our findings from the GARCH-MIDAS-in-Mean model with those obtained from the GARCH-in-Mean model used in *Kontonikas* (*2004*). Our results can be summarised as follows. First, by extending the sample period beyond 2002 (the endpoint used in *Kontonikas 2004*) to 2023, we find that the positive effect of inflation uncertainty on inflation becomes more pronounced in the GARCH-in-Mean model. However, this stronger effect diminishes when the sample excludes either the VAT cut episode or the Covid-19 period. Second, although the results vary across sample periods, we find that realised volatilities contribute meaningfully to long-run inflation uncertainty when the full sample is analysed. Moreover, our analysis shows that macroeconomic and financial variables exert a significant influence on the long-term component of inflation uncertainty. Third, by allowing long-run inflation uncertainty to be time-varying through MIDAS filtering, we observe that the effect of past inflation on current short-run inflation uncertainty becomes insignificant. This result offers a cautionary perspective: evidence suggesting that (short-run) inflation uncertainty rises in response to increases in inflation may partly stem from the restrictive assumption that long-run uncertainty remains constant over time. Nevertheless, we find that inflation uncertainty has a positive and significant effect on inflation in almost all GARCH-MIDAS-in-Mean specifications. Finally, we find no evidence that changes in inflation affect short-run uncertainty.

The rest of the paper is organised as follows: we survey the literature in *Section 2*, *Section 3* introduces the empirical methods, and then *Section 4* describes the data and presents the results. *Section 5* concludes with policy recommendations.

[1] Here, long-run uncertainty is defined as the inflation volatility over a longer horizon, rather than the long-run trend volatility.

2. Literature review

The theoretical underpinnings of the relationship between the level and uncertainty of inflation are strongly debated, with numerous arguments proposing that inflation affects inflation uncertainty, as well as the other way around.

Friedman (*1977*) argues that inflationary pressures often lead to inconsistent and unpredictable responses from monetary authorities, creating heightened uncertainty about future inflation and potentially slowing output growth.[2] *Pourgerami and Maskus* (*1987*), however, point out that a negative effect may exist because higher inflation can incentivise relevant economic agents to invest more in generating accurate predictions.[3]

There are also competing perspectives on how inflation uncertainty can affect inflation itself. *Cukierman and Meltzer* (*1986*) propose a model in which public uncertainty about money supply growth rates and policymakers' objectives can lead to expansionary monetary policies that are designed to surprise the public with inflation. In this framework, higher inflation uncertainty encourages policymakers to enact inflationary surprises to temporarily boost output. By contrast, *Holland* (*1995*) proposes a negative correlation, suggesting that inflation uncertainty can deter inflation. According to Holland, policymakers might avoid inflationary surprises during periods of uncertainty to manage the public's inflation expectations and prevent potential inflationary spirals.

The empirical literature has been steadily expanding, evaluating the latest developments in theoretical models on the link between inflation level and uncertainty.[4] Defining the de-facto standard for analysing the link between inflation and its uncertainty, the ARCH models in *Engle* (*1982*) show that UK inflation has a predictable, time-varying volatility.

Kontonikas (*2004*), for example, uses a GARCH-in-Mean model on UK monthly data to find a positive correlation between past inflation rates and present uncertainty levels. Similarly, *Fountas and Karanasos* (*2007*), studying G7 countries with a univariate GARCH model, observe that inflation tends to increase inflation uncertainty, though they report mixed evidence on whether inflation uncertainty reciprocally influences inflation. *Bredin and Fountas* (*2009*), using a bivariate

[2] *Ball* (*1992*) formalises Friedman's argument within the framework of an asymmetric information game between the public and the policymaker.
[3] This argument is formalised by *Ungar and Zilberfarb* (*1993*).
[4] In most of the empirical literature, inflation uncertainty is defined as the conditional variance of inflation innovations, which differs from monetary policy uncertainty that generally refers to unpredictability in policy decisions or the central bank's reaction function. We thank an anonymous referee for highlighting this important distinction.

GARCH-in-Mean model for EU countries, provide substantial evidence in support of the Cukierman–Meltzer hypothesis, indicating that in many European contexts, inflation uncertainty does indeed foster inflationary pressures as policymakers aim to spur economic growth through inflation surprises. *Fountas et al.* (*2004*) extend this analysis across six EU nations, where they find that inflation consistently increases inflation uncertainty in all countries except Germany, supporting Friedman's hypothesis. However, they obtain limited evidence for the reverse effect, with heterogeneous results regarding inflation uncertainty's influence on inflation across these countries. Moreover, *Daal et al.* (*2005*) examine inflation dynamics in Latin American economies, demonstrating that while inflation typically raises inflation uncertainty, the reverse causality varies, reinforcing the complexity of this relationship, particularly in emerging markets.

Using G7 data, *Balcilar and Ozdemir* (*2013*) employ rolling VAR and MS-VAR models to show that the link between inflation and its uncertainty is time-variant, frequently punctuated by structural breaks. They find strong support for Holland's hypothesis across Canada, France, Germany, Japan, the UK and the US, suggesting that inflation uncertainty can sometimes restrain inflation, while they also confirm Friedman's hypothesis for Canada and the US, where inflation heightens uncertainty. *Caporale and Kontonikas* (*2009*) examine the evolution of this relationship across the euro area, noting heterogeneity across countries and frequent structural breaks, particularly in the lead-up to the introduction of the euro. *Chang* (*2012*), using a modified regime-switching GARCH model, finds that in the US, inflation uncertainty does not significantly impact inflation across various inflationary regimes, underscoring that the inflation-uncertainty dynamic can be regime-dependent.

More recent studies, such as *Barnett et al.* (*2020*), employ semi-parametric approaches across five major developed and emerging economies, identifying a positive short-term to medium-term relationship during stable periods, aligning with Friedman's theory, and a negative relationship during crisis periods. *Apergis et al.* (*2021*), using econometric methods sensitive to structural breaks, identify a unidirectional causality from inflation to inflation uncertainty in Turkey, though this relationship holds only during certain sub-periods. *Bareith and Varga* (*2022*) find that Hungary's inflation-targeting regime significantly reduced core inflation, but had no robust effect on headline inflation or its volatility, with institutional factors such as central bank independence also influencing outcomes. *Sipiczki et al.* (*2024*) examine the exceptionally high inflation in Hungary by disentangling general global drivers from country-specific ("Hungaricum") factors, finding that domestic elements, such as price regulation policies, exchange rate pass-through and fiscal measures, play a significant role alongside international inflationary pressures. *Balatoni and Quittner* (*2024*) analyse the causes of Hungary's 2021–2023 inflation wave, highlighting the combined impact of global supply shocks, energy price surges and domestic factors, such as fiscal stimulus, wage growth and exchange rate depreciation. *Martin and Nagy Mohácsi* (*2024*) evaluate Hungary's inflation-targeting regime and concludes that while it contributed to reducing inflation in the long run, its effectiveness was shaped by broader institutional credibility and the consistency of fiscal and monetary policy alignment.

Taken together, there is considerable literature covering the relationship between inflation and inflation uncertainty, with results varying across domiciles and time. However, the overarching assumption in the literature is that long-term inflation uncertainty is constant. Our contribution is that we relax this assumption and quantify its effect.

3. Econometric framework

Typically, inflation uncertainty is estimated using GARCH models. For instance, *Kontonikas* (2004) employs the following GARCH-in-Mean model to examine the relationship between monthly inflation and inflation uncertainty.

$$\pi_t = \gamma_0 + \gamma_1\pi_{t-1} + \gamma_2\pi_{t-3} + \gamma_3\pi_{t-6} + \gamma_4\pi_{t-12} + \delta\sqrt{\tau h_t} + \mu_t$$

$$h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i\, \mu_{t-i}^2 + \sum_{j=1}^{p} \beta_j\, h_{t-j} + \lambda^\top z_t \tag{1}$$

$$\mu_t = \sqrt{\tau h_t}\varepsilon_t$$

where π_t is the monthly inflation rate at period *t*; τ is a constant measuring the long-run component of inflation uncertainty; h_t denotes the conditional variance of inflation following a GARCH(p,q) process and measuring the short-lived component of inflation uncertainty; z_t is a vector of other exogenous variance regressors; and ε_t is assumed to be *i.i.d.* normal. Note that δ measures the impact of inflation uncertainty on inflation. Furthermore, if we assume that z_t contains only a single variable in this study, namely π_{t-1}, then λ captures the effect of past inflation on current inflation uncertainty. Therefore, *Equation (1)* allows us to explore both directions: a significant λ supports the theory that the level of inflation influences its uncertainty (*Friedman 1977* or *Pourgerami and Maskus 1987*), while a significant δ aligns with the argument that inflation uncertainty affects the level of inflation (*Cukierman and Meltzer 1986* or *Holland 1995*).

However, the above model assumes a constant τ, failing to account for the possibility that short-run and long-run inflation uncertainty may be time-varying, significantly different and influence inflation (expectations) in distinct ways. Therefore, in the spirit of *Engle et al.* (*2013*), we modify *Equation (1)* by incorporating a MIDAS approach to obtain estimates of long-run uncertainty. The model takes the following form:

$$\pi_t = \gamma_0 + \gamma_1 \pi_{t-1} + \gamma_2 \pi_{t-3} + \gamma_3 \pi_{t-6} + \gamma_4 \pi_{t-12} + \delta \sqrt{\tau_t h_t} + \mu_t$$

$$h_t = \alpha_0 + \alpha_1 \mu_{t-1}^2 + \beta_1 h_{t-1} + \lambda^{\top} z_t$$

$$\tau_t = m + \theta \sum_{k=1}^{K} \phi_k\,(\omega_1, \omega_2) x_{t-k} \tag{2}$$

$$\mu_t = \sqrt{\tau_t h_t} \varepsilon_t$$

where ε_t is assumed to be *i.i.d.* normal; for k=1,…,K, $\phi_k(.,.)$ is a weighting function and is known up to parameters (ω_1, ω_2); and x_{t-k} is a MIDAS explanatory regressor. *Equation (2)* offers several analytical and theoretical advantages. First, compared to *Equation (1)*, it allows long-run volatility to evolve over time by incorporating information from high-frequency macro-financial variables through the MIDAS filtering mechanism. Notably, *Equation (2)* nests the conventional GARCH-in-Mean specification as a special case when θ=0. Second, while the number of parameters governing the MIDAS weighting function is fixed, their values are estimated from the data rather than imposed, making the model more parsimonious than complex component volatility models, yet more flexible than approaches with pre-specified weights. As a result, the GARCH-MIDAS framework strikes a useful balance between empirical flexibility and model tractability.

Alternative methods for capturing time-varying long-run components – such as unobserved components models, Kalman filtering, Bayesian time-varying parameter (TVP) models, or smooth transition models – typically rely on latent variables subject to smoothness or trend restrictions. While effective in capturing persistence, these approaches often depend on strong parametric assumptions and utilise filtering techniques that may reduce transparency and hinder economic interpretation.

By contrast, the MIDAS approach links the long-run volatility component directly to observable macro-financial variables sampled at higher frequencies. This strategy provides several practical advantages: (i) it avoids arbitrary trend specifications; (ii) it enhances transparency by defining the long-run component as a function of measurable indicators; (iii) it flexibly accommodates time-varying contributions from different predictors through a parsimonious lag weighting structure; and

(iv) it is computationally efficient and compatible with quasi-maximum likelihood estimation. Anchoring long-run volatility in actual economic data rather than abstract latent constructs makes MIDAS a more interpretable and policy-relevant tool. It also aligns closely with the real-time forecasting practices employed by central banks and policy institutions. In this regard, the GARCH-MIDAS specification offers a robust, transparent alternative to more opaque, latent-variable models for modelling persistent volatility dynamics.

Following *Ghysels et al.* (*2004*) and *Engle et al.* (*2013*), we empirically employ a Beta function to specify the weighting scheme with the following form for our study:

$$\phi_k(\omega_1, \omega_2) = \frac{(k/K)^{\omega_1 - 1}(1 - k/K)^{\omega_2 - 1}}{\sum_{k=1}^{K} (k/K)^{\omega_1 - 1} (1 - k/K)^{\omega_2 - 1}}.$$

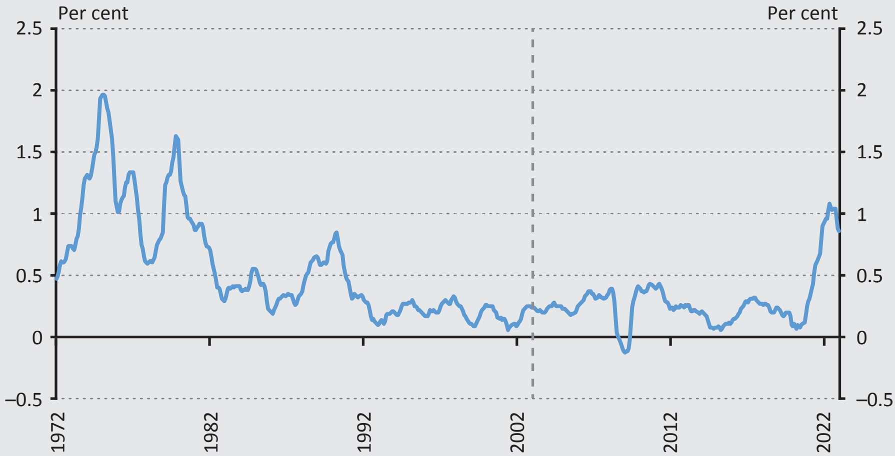
In practice, x_t may be in high-dimensional. In that case, an unsupervised machine learning method may be applied for dimensionality reduction. For instance, one can apply principal component analysis (PCA) to x_t as a first step. Then, one can use the first principal component (see, for instance, *Chen et al. 2023b*) as the latent MIDAS predictor.

4. Estimation results

This section presents the data and the estimation results. We obtain the monthly (seasonally-adjusted) UK inflation data used in our study from the Global Financial Database, covering the period 1972 to 2023, which is defined as $\pi_t = (CPI_t - CPI_{t-1})/CPI_{t-1} \times 100$. *Figure 1* shows month-on-month inflation in the UK between 1972 and 2023, where the dashed vertical line shows the end date of the sample used in *Kontonikas* (*2004*).

Consistent with *Kontonikas* (*2004*), between 1972 and 2003, we observe that periods of higher average inflation correspond to periods of more volatile inflation. Moreover, both inflation on short and long horizon are particularly volatile before the adoption of inflation targeting (1992). After 2003, however, we find that the inflation rate on long horizon remains low and tends to be much smoother than the rate on short horizon, except for the temporary shocks of the Global Financial Crisis and the recent turmoil (i.e. the Covid-19 pandemic and the Russo-Ukrainian War). Visual inspection of the plot indicates that the long-run volatility of the inflation rate is indeed time-varying.

Figure 1
Month-on-month inflation in the United Kingdom between 1972 and 2023



Note: The vertical dashed line shows the end date of the original sample.

An important question arises: Could macroeconomic and financial variables drive long-run inflation uncertainty, and if so, how might this influence the inflation-uncertainty nexus? To investigate this, we draw on previous research (e.g. *Baker et al. 2016*; *Grimme et al. 2014*; *Chen et al. 2023b*) and select the following macro-finance variables as potential contributors to long-run component uncertainty: UK economic policy uncertainty (EPU), the yield spread (defined as the difference between the three-month interbank rate and the three-month Treasury bill yield) and the CBOE[5] Volatility Index (VIX) as MIDAS explanatory variables.[6] To account for data availability, we collect the data from 2003 to 2023 for the above macro-finance variables. *Table 1* shows the descriptive statistics of the variables.

[5] Chicago Board Options Exchange
[6] The yield spread, defined as the difference between the three-month interbank rate and the three-month Treasury bill rate, is commonly interpreted as an indicator of short-term funding stress and risk premia. It tends to widen during episodes of financial market stress and uncertainty, thus providing a forward-looking signal of deteriorating financial conditions that often coincide with heightened macroeconomic and inflation uncertainty. For the empirical estimation, we rescale the values of EPU and VIX by applying the monotonic transformation log(EPU + 1) * 0.01 to the EPU variable and log(VIX) * 0.01 to the VIX. Without these transformations, the large magnitudes of the raw variables distort the estimation results. We thank an anonymous referee for bringing this issue to our attention.

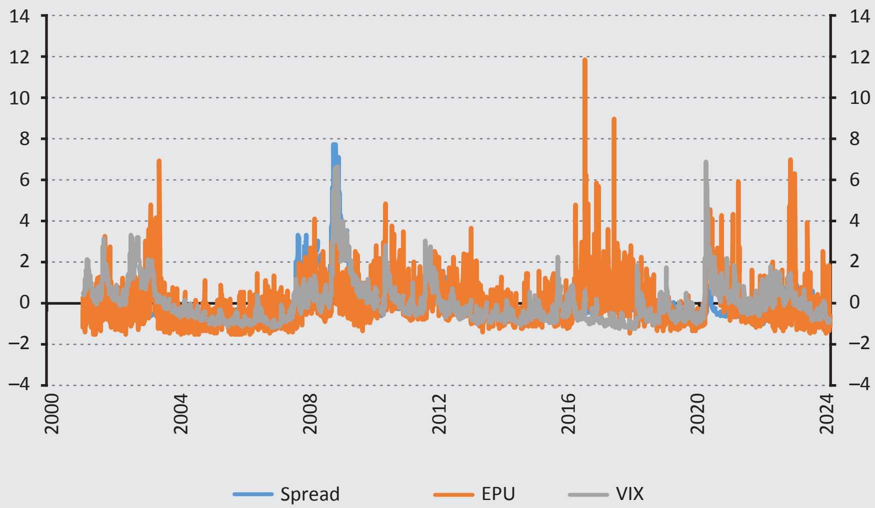
Table 1
Descriptive statistics

	Mean	Std.Dev	Min	Max	Variance	Skewness	Kurtosis
π	0.4666	0.4003	–0.1264	2.0041	0.1602	1.6157	2.2566
EPU	294.7170	194.7631	0.0000	2,610.0600	37,932.6448	2.1686	11.5161
Spread	0.2321	0.3391	–0.1213	2.8613	0.1150	3.8254	19.0868
VIX	20.2523	9.0781	9.1400	82.6900	82.4125	2.0400	6.3582

Note: The rows present descriptive statistics for various economic and financial indicators.

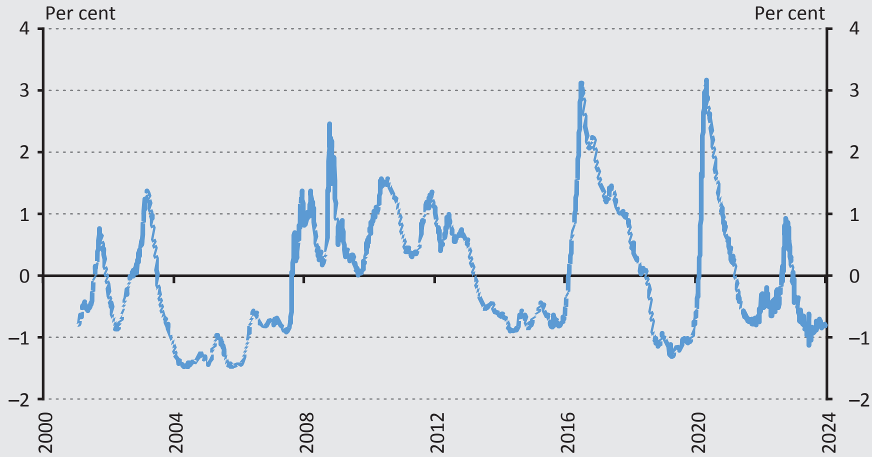
Figure 2 plots the standardised values of the EPU index, yield spread and VIX. *Figure 3* displays the first principal component extracted from these macro-financial variables, capturing their common factor. Over the period from 2003 to 2023, peaks in the individual series – particularly during episodes of global financial stress such as in 2008, 2012 and 2020 – tend to coincide with elevated month-on-month inflation. The first principal component reflects these synchronised spikes, indicating a strong co-movement between macro-financial uncertainty and inflationary pressures during turbulent periods.

Figure 2
Standardised values of high-frequency macro-financial indicators



Note: The series are standardised and cover the period from 2001 to 2023.

Figure 3
Common factor in high-frequency macro-financial indicators



Note: The series are standardised and cover the period from 2001 to 2023.

The literature has long documented mixed evidence on whether the UK inflation rate is stationary, depending on the sample period. *Joyce* (*1995*) found that augmented *Dickey–Fuller* (ADF) tests fail to reject the null hypothesis of a unit root over the period 1976–1994. *Grier and Perry* (*1998*) reported that CPI inflation is non-stationary over the post-WWII period, while *Kontonikas* (*2004*) found that both ADF and Phillips–Perron tests (PP) strongly reject the null over 1972–2002. Therefore, we conduct both full and period-based ADF unit root tests for π, and *Table 2* presents the results. Consistent with *Kontonikas* (*2004*), the ADF tests strongly reject the null of a unit root over the same period. The results also show that UK inflation was stationary before Covid-19. However, in the Covid-19 and post-Covid period (2019–2023), the test fails to reject nonstationarity.

Table 2
ADF unit root test, π across full and different subperiods

	Full	1972–2002	2002–2019	2019–2023
ADF statistic	–4.35***	–4.82***	–4.10***	–0.90
p-value	0.00	0.00	0.01	0.96
Lags	5	5	5	5
Observations	606	366	198	30
Crit. val. 1%	–3.97	–3.98	–4.01	–4.30
Crit. val. 5%	–3.42	–3.42	–3.43	–3.57
Crit. val. 10%	–3.13	–3.13	–3.14	–3.22

*Note: The ADF regressions include an intercept and a trend, with the optimal lag length selected based on the AIC criterion using up to five lags. The full period covers 1972–2023. *, **, and *** indicate rejection of the null hypothesis of a unit root at the 10%, 5%, and 1% levels of significance, respectively.*

We also employ the ADF test to assess the stationarity of the high-frequency macro-financial variables used in the MIDAS components. The results, reported in *Table 3*, indicate that the null hypothesis of a unit root is rejected for all variables (at least at the 10-per cent significance level), suggesting that all series are stationary.

Table 3
ADF unit root test, high-frequency variables

	Spread	EPU	VIX
ADF statistic	–3.25*	–12.05***	–5.84***
p-value	0.07	0.00	0.00
Lags	4	5	5
Observations	5,718	5,717	5,717
Crit. val. 1%	–3.98	–3.96	–3.96
Crit. val. 5%	–3.411	–3.411	–3.411
Crit. val. 10%	–3.128	–3.128	–3.128

*Note: The ADF regressions include an intercept and a trend, with the optimal lag length selected based on the AIC criterion using up to five lags. The period covers 1972–2023. *, **, *** and indicate rejection of the null hypothesis of a unit root at the 10%, 5%, and 1% levels of significance, respectively.*

We proceed with an extension of *Kontonikas* (*2004*), using a GARCH-in-Mean model with data up to 2023.[7] The results are summarised in *Table 4*. Specifically, we report the results for the original period, as defined in *Kontonikas* (*2004*), which spans from 1972 to 2002. Our extended period ("Full") expands this time frame to cover 1972 through 2023. The "Exclude Tax Cut" specification omits observations around the VAT cut implemented in the UK in 2009, while the "Exclude Covid" sample ends in December 2019 to avoid pandemic-related distortions.[8] Consistent with *Kontonikas* (*2004*), the estimated λ is positive and significant at the 1-per cent level, supporting the Friedman–Ball hypothesis. Notably, our findings also align with the Cukierman–Meltzer prediction, revealing that inflation uncertainty has a positive and significant effect on average inflation. To address concerns about potential structural breaks, such as the temporary VAT cut in 2009 and the Covid-19 pandemic, we conduct additional estimations that exclude these periods. The results, presented in *Table 4*, indicate that the estimates for *λ* and *δ* remain generally positive and statistically significant, reinforcing the main conclusions. In particular, the positive effect of δ becomes more pronounced when the sample period is extended from 2002 to 2023. However, this stronger effect diminishes once the observations associated with the VAT cut or the Covid-19 crisis are excluded.

[7] *Kontonikas* (*2004*) shows that, in most cases, when a GARCH(1,1) is used, the Ljung-Box statistics of the standardised and the squared standardised residuals are all insignificant, indicating proper model specification. Consistent with *Kontonikas* (*2004*), we choose the GARCH(1,1) specification of *Equation (1)*.
[8] We employ a Wald statistic to test the parameter restriction under the null hypothesis that $\alpha_1 + \beta_1 = 1$. In all cases, the null is rejected, supporting the stability of the GARCH(1,1) specification.

Table 4
GARCH-in-Mean model estimation results

z_t	π_{t-1}			
	Original Period	Extended Period		
		Exclude Tax Cut	Exclude Covid	Full
γ_0	–0.0022	0.0006	–0.0024	–0.0031
	(0.0040)	(0.0033)	(0.0037)	(0.0045)
γ_1	1.2686***	1.2612***	1.2555***	1.2407***
	(0.0346)	(0.0282)	(0.0380)	(0.0408)
γ_2	–0.2679***	–0.2535***	–0.2511***	–0.2299***
	(0.0470)	(0.0388)	(0.0485)	(0.0518)
γ_3	–0.0471**	–0.0496***	–0.0331*	–0.0464**
	(0.0261)	(0.0210)	(0.0208)	(0.0212)
γ_4	0.0238**	0.0176**	0.0097	0.0120*
	(0.0102)	(0.0084)	(0.0077)	(0.0087)
δ	0.3906**	0.3313**	0.3381**	0.4454**
	(0.2128)	(0.1979)	(0.1898)	(0.2153)
α_0	0.0001	0.0001**	0.0001***	0.0002***
	(0.0001)	(0.0000)	(0.0000)	(0.0000)
α_1	0.5438***	0.5663***	0.6542***	0.6288***
	(0.1290)	(0.1068)	(0.1191)	(0.1171)
β_1	0.0935	0.1184**	0.1011**	0.0980**
	(0.0828)	(0.0607)	(0.0530)	(0.0572)
λ	0.0008***	0.0008***	0.0005***	0.0005***
	(0.0002)	(0.0001)	(0.0001)	(0.0001)
Wald statistic	5.6002**	6.5881**	3.5224*	4.3986**
p-value	0.0180	0.0103	0.0605	0.0360

*Note: The standard errors are shown in parentheses. *, **, and *** indicate rejection of the null hypothesis of a unit root at the 10%, 5%, and 1% levels of significance, respectively. The original period, as covered in Kontonikas (2004), spans from 1972 to 2002. Our extended period (Full) expands this timeframe to cover 1972 through 2023. Exclude Tax Cut excludes the VAT cut in 2009 in the UK, and Exclude Covid spans until December 2019. Wald test for stationarity: Null hypothesis is $\alpha_1 + \beta_1 = 1$. Reported values are the Wald test statistics and p-values.*

Recognising the limitations of the GARCH model, which assumes constant long-term uncertainty, we employ a GARCH-MIDAS model to re-examine the inflation-inflation uncertainty relationship. *Table 5* provides the GARCH-MIDAS results using realised volatility as an explanatory factor for long-term inflation volatility.[9] Since monthly realised volatilities tend to be noisy, MIDAS filtering applies (MIDAS) weighted averages to create a smoothed volatility measure. Interestingly, we find that the estimate of the parameter θ is significant when using the full extended sample period, suggesting that the weighted average of realised volatilities contributes meaningfully to long-run inflation uncertainty over this horizon. However, this effect becomes insignificant when we restrict the estimation to the original sample period (1972–2002) or to the extended period excluding either the VAT tax cut or the Covid episode. Notably, the estimate of λ in the GARCH-MIDAS-in-Mean model also loses significance, implying that past inflation cannot predict short-run inflation uncertainty once long-run components are allowed to be time-varying. Importantly, this does not necessarily mean that the results from the GARCH-MIDAS-in-Mean specification contradict the Friedman–Ball hypothesis. Rather, they provide a cautionary perspective: the evidence that inflation raises expected short-run inflation uncertainty, as captured by the significant λ coefficient in the conventional GARCH-in-Mean model, may partly reflect the restriction of assuming a constant long-run inflation uncertainty component. Once this restriction is relaxed, the impact of inflation on expected short-run inflation uncertainty becomes less pronounced. This finding highlights the importance of carefully distinguishing between short-run and long-run components of uncertainty when evaluating the inflation-uncertainty relationship.

[9] The effective data spans from 1976 to 2023.

Table 5
GARCH-MIDAS-in-Mean model estimation results: RV as conditioning variable in MIDAS

z_t	π_{t-1}			
	Original Period	Extended Period		
		Exclude Tax Cut	Exclude Covid	Full
γ_0	–0.0047	0.0046	0.0041*	0.2924***
	(0.0066)	(0.0039)	(0.0030)	(0.0090)
γ_1	1.2150***	1.2128***	1.2298***	–0.0038
	(0.0404)	(0.0385)	(0.0332)	(0.0084)
γ_2	–0.2086***	–0.1961***	–0.2301***	0.2452
	(0.0569)	(0.0505)	(0.0449)	(0.1938)
γ_3	–0.0697**	–0.0612***	–0.0391*	–0.2667*
	(0.0347)	(0.0249)	(0.0249)	(0.1885)
γ_4	0.0133	0.0047	0.0029	–0.1298
	(0.0151)	(0.0107)	(0.0113)	(0.1057)
δ	0.8522**	0.3227*	0.2621*	0.3306***
	(0.3832)	(0.2018)	(0.1774)	(0.0553)
α_0	–0.0006	0.0350	0.1442	0.3308***
	(0.0013)	(0.1554)	(0.9289)	(0.0266)
α_1	0.3756***	0.5039***	0.4221***	0.2133***
	(0.1280)	(0.1256)	(0.1049)	(0.0352)
β_1	0.0436	0.0901	0.0000	0.0000
	(0.1299)	(0.1054)	(0.1635)	(0.1262)
λ	–0.0010	0.1773	0.1767	0.0591
	(0.0024)	(0.7820)	(1.1563)	(0.1877)
m	–0.2283	0.0030	0.0009	0.0030***
	(0.5234)	(0.0133)	(0.0060)	(0.0000)
θ	–0.3357	0.0008	0.0021	0.3492***
	(0.9653)	(0.0037)	(0.0134)	(0.0589)
ω_1	4.5093**	4.5016	4.5175	4.5190
	(2.4549)	(6.1963)	(6.2885)	(3.6012)
ω_2	2.7584	2.7864	2.7623	2.7630
	(6.3777)	(10.6942)	(5.4596)	(2.2411)

*Note: The standard errors are shown in parentheses. *, **, and *** indicate rejection of the null hypothesis of a unit root at the 10%, 5%, and 1% levels of significance, respectively. This table shows the GARCH–MIDAS-in-Mean estimation results, using realised volatility as the explanatory variable in the MIDAS component. The original period, as covered in Kontonikas (2004), spans from 1972 to 2002. Our extended period (Full) expands this timeframe to cover 1976 through 2023. Exclude Tax Cut excludes the VAT cut in 2009 in the UK, and Exclude Covid spans until December 2019.*

A key question we need to address is whether macroeconomic and financial variables can impact long-run inflation uncertainty, and if they do, how this might shape the relationship between inflation and uncertainty. To explore this, we consider using macro-finance variables (as discussed above) as explanatory variables.[10] *Table 6* presents the GARCH-MIDAS results, showing that the weighted average of both the EPU and the yield spread significantly affects the volatility of long-term inflation. This finding suggests that long-run volatility indeed varies with macroeconomic and financial conditions.[11] Consistent with the findings using realised volatility as the explanatory variable, we find that λ is insignificant across all specifications. This suggests that once the model flexibly allows for time-varying long-run uncertainty, the evidence that short-run uncertainty drives higher inflation becomes substantially weaker. Regarding reverse causality, we observe that inflation uncertainty exerts a positive impact on inflation when the long-term component of uncertainty is modelled as a function of the EPU or the yield spread, consistent with the hypothesis of *Cukierman and Meltzer* (*1986*). However, this effect disappears when the VIX is used as the conditioning variable.

While persistent inflation is generally linked to the formation of long-run inflation uncertainty, changes in inflation are more intuitively connected to short-run inflation uncertainty. Therefore, we also assess the relationship between changes in inflation and short-run inflation uncertainty and reported the results in *Table 7*.[12] Similar to the previous analyses, we utilise three macroeconomic and financial variables. As *Table 7* illustrates, the λ estimates across all specifications are insignificant, indicating that inflation changes do not affect future short-run inflation uncertainty. Meanwhile, the Cukierman–Meltzer prediction holds across all models except the VIX.

[10] Although τ_t is introduced and interpreted as long-run inflation uncertainty within our framework, it is important to note that it is estimated using macrofinancial variables – namely EPU, VIX and the yield spread. Therefore, τ_t may also be viewed more broadly as a measure of persistent macrofinancial uncertainty, or its trend, which often overlaps with inflation uncertainty but is not limited to it. This broader interpretation is justified by the strong co-movement observed between these variables and inflation dynamics during periods of financial stress. Accordingly, τ_t should be interpreted as a latent factor capturing both long-run inflation uncertainty and more general macro-financial risk conditions that influence expectations and volatility in the inflation process. We thank an anonymous referee for pointing this out.

[11] While τ_t is constructed to represent long-run inflation uncertainty, it is derived from macrofinancial variables that themselves may reflect broader economic and financial conditions. Therefore, τ_t may simultaneously capture co-movements arising from shared underlying shocks. As such, the results should be interpreted as conditional correlations rather than structural causal effects.

[12] The only difference between the specifications in *Table 6* and *Table 7* lies in the definition of the variable z_t: while *Table 6* uses lagged inflation π_{t-1}, *Table 7* replaces it with the absolute change in inflation, $|\Delta\pi_{t-1}|$.

Table 6
GARCH-MIDAS-in-Mean model estimation results: Recent period (2001–2023) with different conditioning variables in MIDAS

z_t	π_{t-1}			
	GARCH-in-Mean	GARCH-MIDAS-in-Mean		
		EPU	Spread	VIX
γ_0	0.0072	0.0199***	0.0880**	0.0082**
	(0.0343)	(0.0052)	(0.0509)	(0.0045)
γ_1	1.1619***	0.5028***	–0.0420	1.2009***
	(0.2038)	(0.1217)	(0.4031)	(0.0661)
γ_2	–0.1360	0.5634***	0.2075	–0.1884**
	(0.1848)	(0.1492)	(0.5869)	(0.0920)
γ_3	–0.0547***	–0.0792*	–0.3043	–0.0365
	(0.0113)	(0.0580)	(0.4530)	(0.0379)
γ_4	–0.0170*	–0.1180***	–0.1657	–0.0197
	(0.0104)	(0.0438)	(0.3382)	(0.0176)
δ	0.2479**	0.3064***	0.3716***	0.1860
	(0.1140)	(0.0336)	(0.0807)	(0.3536)
α_0	0.0002***	0.0762*	0.4197***	0.1219
	(0.0000)	(0.0473)	(0.1178)	(0.2580)
α_1	0.8146**	1.0000***	0.2019***	0.5364***
	(0.4843)	(0.1687)	(0.0281)	(0.2019)
β_1	0.0000	0.0911***	0.2004	0.0731
	(0.4654)	(0.0373)	(0.1643)	(0.1188)
λ	0.0004**	0.0167	0.0875	0.2443
	(0.0002)	(0.1740)	(0.1943)	(0.5205)
m		–0.0172***	0.0141**	–0.0044*
		(0.0000)	(0.0055)	(0.0094)
θ		0.3638***	0.4171***	0.2185
		(0.0012)	(0.1564)	(0.4622)
ω_1		4.5184***	4.5190	4.5199
		(1.3027)	(4.3355)	(10.7931)
ω_2		2.7636***	2.7630	2.7582
		(0.7527)	(3.0131)	(4.7358)

*Note: The standard errors are shown in parentheses. *, **, and *** indicate rejection of the null hypothesis of a unit root at the 10%, 5%, and 1% levels of significance, respectively. This table shows the GARCH-in-mean and GARCH-MIDAS-in-Mean estimation results. For the GARCH-MIDAS-in-Mean, the Economic Policy Uncertainty Index (EPU), the Ted Spread (Spread) and the CBOE Volatility Index (VIX) served as the explanatory variable in the MIDAS component, respectively. The period spans from 2001 to 2023.*

Table 7
GARCH-MIDAS-in-Mean model estimation results: Recent period (2001–2023) with different conditioning variables in MIDAS, z_t=|$\Delta\pi_{t-1}$|

z_t	$\Delta\pi_{t-1}$			
	GARCH-in-Mean	GARCH-MIDAS-in-Mean		
		EPU	Spread	VIX
γ_0	0.0120***	0.0175***	0.0989***	0.0076***
	(0.0038)	(0.0021)	(0.0353)	(0.0021)
γ_1	1.2062***	0.5273***	–0.0342	1.1821***
	(0.0520)	(0.0713)	(0.3337)	(0.0499)
γ_2	–0.2139***	0.5368***	0.2149	–0.1696***
	(0.0740)	(0.1844)	(0.5003)	(0.0686)
γ_3	–0.0222	–0.0866	–0.2978	–0.0352
	(0.0348)	(0.2129)	(0.4105)	(0.0333)
γ_4	–0.0142	–0.1186	–0.1617	–0.0200
	(0.0142)	(0.1072)	(0.3198)	(0.0178)
δ	–0.0286	0.3506***	0.3717***	0.1902
	(0.1524)	(0.0579)	(0.1299)	(0.1865)
α_0	0.0002***	0.1105***	0.4063**	0.0914
	(0.0001)	(0.0341)	(0.2134)	(0.3320)
α_1	0.6951***	1.0000***	0.2054***	0.5709***
	(0.2251)	(0.0779)	(0.0266)	(0.1943)
β_1	0.0000	0.0398***	0.1982	0.0114
	(0.0175)	(0.0061)	(0.3589)	(0.0476)
λ	0.0062	0.1282	0.1293	0.2039
	(0.0050)	(0.1512)	(3.8907)	(1.2992)
m		–0.0145***	0.0058	–0.0096
		(0.0000)	(0.0215)	(0.0315)
θ		0.3055***	0.4147**	0.4776
		(0.0000)	(0.2292)	(1.5969)
ω_1		4.5213***	4.5190	4.5181
		(0.9698)	(7.4625)	(11.7613)
ω_2		2.7589***	2.7631	2.7637
		(0.2886)	(2.5563)	(6.5527)

*Note: The standard errors are shown in parentheses. *, **, and *** indicate rejection of the null hypothesis of a unit root at the 10%, 5%, and 1% levels of significance, respectively. This table shows the GARCH-in-Mean and GARCH-MIDAS-in-Mean estimation results. z_t=|$\Delta\pi_{t-1}$|. For the GARCH-MIDAS-in-Mean, the Economic Policy Uncertainty Index (EPU), the Ted Spread (Spread) and the CBOE Volatility Index (VIX) served as the explanatory variable in the MIDAS component, respectively. The period spans from 2001 to 2023.*

5. Conclusion

This paper revisits the relationship between inflation and inflation uncertainty using a GARCH-MIDAS-in-Mean approach with UK data, allowing us to decompose inflation uncertainty into short-term and time-varying long-term components. We find that macroeconomic and financial variables significantly impact long-term inflation uncertainty. Furthermore, the empirical analysis shows that the standard GARCH-in-Mean model finds a positive and significant effect of inflation on inflation uncertainty, consistent with the Friedman–Ball hypothesis. However, when short-run inflation uncertainty is separated from time-varying long-run uncertainty, the evidence that past inflation increases short-term uncertainty becomes much weaker. This suggests that the Friedman–Ball hypothesis may apply mainly to long-run inflation uncertainty rather than short-term fluctuations. Additionally, we find strong evidence of a positive impact of inflation uncertainty on inflation, providing support for the Cukierman–Meltzer hypothesis.

Our evidence shows that long-run inflation uncertainty is time-varying and that uncertainty feeds back into inflation. This suggests that policy should target the determinants of the long-run component. First, stabilise and clearly communicate the reaction function (i.e. rules-based decisions and state-contingent forward guidance) to anchor expectations and lower policy uncertainty. Second, coordinate monetary and fiscal measures (e.g. VAT changes) and pre-announce time paths to avoid surprise regime shifts that create structural breaks. Third, embed a real-time MIDAS-style dashboard (EPU, yield spread, market volatility) into the policy process and publish it so that reducing long-run uncertainty becomes an explicit intermediate objective. Fourth, when shocks hit, favour automatic stabilisers and targeted measures with sunset clauses over discretionary packages that are hard to forecast. Finally, since short-run inflation does not reliably raise short-run uncertainty once long-run variation is modelled, avoid overreacting to transitory price spikes and focus on anchoring the longer-horizon component.

This analysis can be extended in several directions. First, while we allow nonlinearity within the MIDAS weighting function, the long-run volatility is essentially assumed to be linear given the weighting scheme. Extending the MIDAS to a nonlinear framework through a regime-switching model as in *Pan et al.* (*2017*), a threshold model as in *Chen et al.* (*2023a*) or a kink model as in *Zhang et al.* (*2024*) would be an interesting avenue for future research. Second, while this paper focuses on the UK, it would be worthwhile to extend the model to a panel setup and use global data to re-examine this nexus. Third, in this paper, we focus exclusively on the impact of inflation on short-run uncertainty, without examining the long-run uncertainty. It would be intriguing to investigate how past inflation affects both the short-run and long-run components of uncertainty by introducing lagged inflation as an additional regressor into the MIDAS model. We leave these possibilities for future research.

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