Commodity Exchange-Traded Commodities and Euro Area Inflation Nowcasting: A MIDAS Approach

Abstract

This paper investigates whether high-frequency information from commodity exchange-traded commodities (ETCs) can improve the nowcasting of euro area inflation. Using monthly Harmonised Index of Consumer Prices (HICP) data and daily commodity ETC returns from September 2012 to 2025, we examine the predictive content of three major commodity groups: energy, agriculture, and industrial metals. To exploit the mixed-frequency nature of the data, we employ a Mixed Data Sampling (MIDAS) framework that incorporates daily commodity returns into monthly inflation forecasts. The analysis proceeds in three stages. First, we assess the relationship between commodity returns and inflation through a baseline regression. Second, we estimate Beta-MIDAS specifications using daily commodity information. Third, we conduct a real-time nowcasting exercise at different points within the month and compare forecasting performance against standard benchmark models, including an AR(1) specification and a random walk forecast. The results indicate that energy commodity returns exhibit the strongest relationship with inflation dynamics, whereas agricultural and industrial metal commodities provide weaker signals. Although commodity prices contain economically meaningful information about inflation pressures, the MIDAS specifications do not outperform simple benchmark models in out-of-sample forecasting exercises. Overall, the findings suggest that commodity markets provide useful real-time information on inflation developments, but that translating such information into superior forecasting performance remains challenging due to the persistence of inflation and the noisy nature of high-frequency financial data.

1. Introduction

Inflation forecasting plays a central role in macroeconomic analysis and in the conduct of monetary policy. Accurate and timely information on inflation dynamics is essential for policymakers, as inflation expectations influence the decisions of households, firms, and financial market participants. However, official inflation statistics are typically released at a monthly frequency and with a delay, which limits the ability to monitor inflation developments in real time. This limitation has motivated the development of nowcasting approaches aimed at extracting timely information from higher-frequency data sources (Modugno, 2011; Aliaj et al., 2023). In recent years, the increasing availability of high-frequency data has significantly improved the scope for real-time macroeconomic monitoring. Nowcasting has become a widely used tool in central banks and international institutions, as it allows incorporating newly available information into forecasts as it arrives (Knotek and Zaman, 2017). A key advantage of nowcasting models is their ability to exploit data sampled at different frequencies, thereby enriching the information set used for short-term forecasting. The use of mixed-frequency data introduces important econometric challenges, as macroeconomic variables are typically observed at lower frequencies than financial variables. Mixed Data Sampling (MIDAS) regressions provide a natural framework to address this issue, allowing high-frequency variables to enter directly into models explaining lower-frequency outcomes without requiring aggregation (Ghysels et al., 2004; Foroni et al., 2018). These models offer a parsimonious way to incorporate a large number of high-frequency observations through flexible weighting schemes, preserving valuable information that would otherwise be lost through temporal aggregation. Financial markets represent a particularly relevant source of high-frequency information. Asset prices are inherently forward-looking and reflect expectations about future economic conditions, making them potentially informative predictors of macroeconomic variables (Andreou et al., 2013). In particular, commodity prices have long been recognized as key determinants of inflation dynamics, as they directly affect production costs and consumer prices. Empirical evidence shows that commodity futures returns are positively correlated with inflation and can act as a hedge against unexpected inflation (Gorton and Rouwenhorst, 2006). Among commodities, energy prices play a particularly important role. Energy inflation is a major source of volatility in headline inflation and a key driver of forecast errors, highlighting the importance of modeling energy price dynamics accurately (Bańbura et al., 2025). Recent evidence further emphasizes the importance of global commodity price shocks and import prices in explaining inflation developments in the euro area, especially during the post-pandemic period (Hansen et al., 2023). In addition, the literature has documented significant pass-through effects from commodity prices, both energy and food, to consumer prices, although the strength and timing of this transmission may vary across sectors (Ferrucci et al., 2010; López et al., 2024). Despite the availability of high-frequency data and advanced econometric techniques, forecasting inflation remains a difficult task. A large literature documents that simple benchmark models, such as autoregressive specifications or random walk processes, are often difficult to outperform in practice (Knotek and Zaman, 2017). This reflects the strong persistence of inflation dynamics and the challenges associated with extracting useful signals from noisy high-frequency indicators. Recent contributions have attempted to address these challenges by incorporating large information sets and applying regularization or machine learning techniques, such as Lasso-based VAR models, to improve forecasting performance in high-dimensional settings (Aliaj et al., 2023). Against this background, this paper investigates whether high-frequency commodity prices can improve the nowcasting of euro area inflation. Specifically, we examine whether daily returns of exchange-traded commodity products (ETCs) contain useful information for predicting monthly inflation, as measured by the Harmonised Index of Consumer Prices (HICP). By combining financial market data with macroeconomic indicators in a mixed-frequency framework, we aim to assess the extent to which commodity price movements anticipate inflation developments. The empirical analysis uses data from September 2012 to 2025 and focuses on three broad commodity groups: energy, agriculture, and industrial metals. We employ MIDAS regressions to incorporate daily commodity returns into a monthly inflation model and conduct a real-time nowcasting exercise at different points within the month. The predictive performance of the MIDAS specification is evaluated against standard benchmark models, including autoregressive and random walk forecasts.

2. Related Literature

This paper contributes to three interconnected strands of literature: mixed-frequency econometric models, inflation nowcasting, and the relationship between commodity markets and inflation dynamics. The first strand concerns the development of mixed-frequency econometric techniques. The seminal contribution of Ghysels, Santa-Clara and Valkanov (2004) introduced the Mixed Data Sampling (MIDAS) framework, which allows researchers to exploit high-frequency information without requiring temporal aggregation of the explanatory variables. By modelling the lag structure through a parsimonious weighting scheme, MIDAS regressions provide an efficient approach to combining variables observed at different frequencies. Subsequent contributions extended the original framework. Foroni, Marcellino and Schumacher (2011) proposed the U-MIDAS specification, which relaxes the parametric restrictions imposed on lag weights and allows for greater flexibility when sufficient observations are available. Further developments by Foroni, Marcellino and Stevanović (2018) incorporated moving-average components into mixed-frequency models, improving forecasting performance in the presence of serially correlated disturbances. A second strand of literature focuses on inflation nowcasting. Modugno (2011) demonstrates how high-frequency indicators can significantly improve short-term inflation estimates through dynamic factor models that continuously incorporate newly available information. More recently, Linzenich and Meunier (2025) developed a comprehensive nowcasting toolbox combining factor models, bridge equations and mixed-frequency approaches to enhance real-time forecasting performance. Additional contributions include Beck et al. (2024), who show that high-frequency scanner data can improve inflation nowcasts, and Aliaj, Ciganovic and Tancioni (2023), who employ Lasso-regularized mixed-frequency models to produce accurate real-time forecasts of euro area inflation. Knotek and Zaman (2017) further demonstrate that the predictive accuracy of inflation nowcasts improves progressively as information accumulates throughout the month. The third strand of literature investigates the role of commodity markets in explaining inflation dynamics. Ferrucci, Jiménez-Rodríguez and Onorante (2010) document a significant pass-through from agricultural commodity prices to consumer prices in the euro area. More recently, López, Odendahl, Párraga and Silgado-Gómez (2024) show that gas price shocks exert a substantial influence on euro area inflation, particularly through indirect effects operating via production costs. Similarly, Bańbura et al. (2025) highlight the importance of high-frequency energy indicators for forecasting energy inflation, while Hansen, Toscani and Zhou (2023) identify international commodity prices as one of the key drivers behind the post-pandemic inflation surge in the euro area. These studies collectively suggest that commodity prices contain valuable information about inflationary pressures and may therefore contribute to real-time inflation monitoring. Finally, the present paper also relates to the broader literature on commodity markets as financial assets. Gorton and Rouwenhorst (2006) show that commodity futures exhibit a positive relationship with inflation, while Hamilton and Wu (2014) analyse the growing financialisation of commodity markets and its implications for commodity price dynamics. Building on these contributions, this study examines whether daily returns on commodity exchange-traded commodities (ETCs) can provide useful information for nowcasting euro area inflation within a MIDAS framework. Unlike most existing studies, which focus on commodity spot prices, futures contracts or broad commodity indices, this paper evaluates the informational content of tradable ETC instruments across energy, agricultural and industrial metal markets.

3. Data

This study combines monthly inflation data with daily financial market information from commodity exchange-traded products (ETCs). The use of mixed-frequency data allows us to investigate whether high-frequency movements in commodity markets contain useful information for nowcasting inflation in the euro area. This approach is consistent with the growing literature emphasizing the importance of combining high-frequency financial variables with lower-frequency macroeconomic indicators in forecasting applications (Andreou et al., 2013; Ghysels et al., 2004). Inflation is measured using the Harmonised Index of Consumer Prices (HICP) for the euro area, obtained from Eurostat. The HICP represents the standard measure of consumer price inflation used by the European Central Bank for monetary policy analysis. The inflation series is observed at monthly frequency. To capture high-frequency information from commodity markets, we use daily returns of exchange-traded commodity products (ETCs). These instruments track the price dynamics of underlying commodity futures and provide a liquid and forward-looking measure of commodity market expectations.

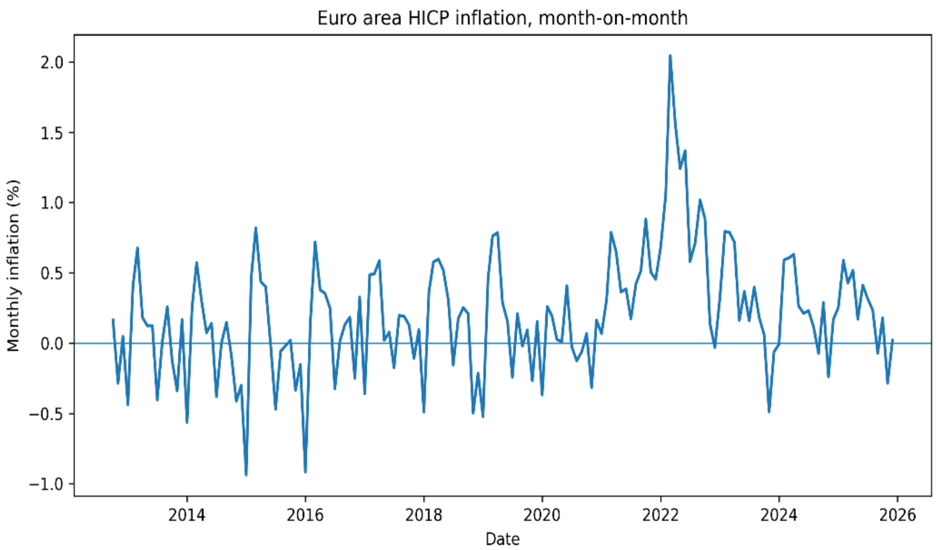

Figure 1. Monthly HICP inflation in the Euro Area

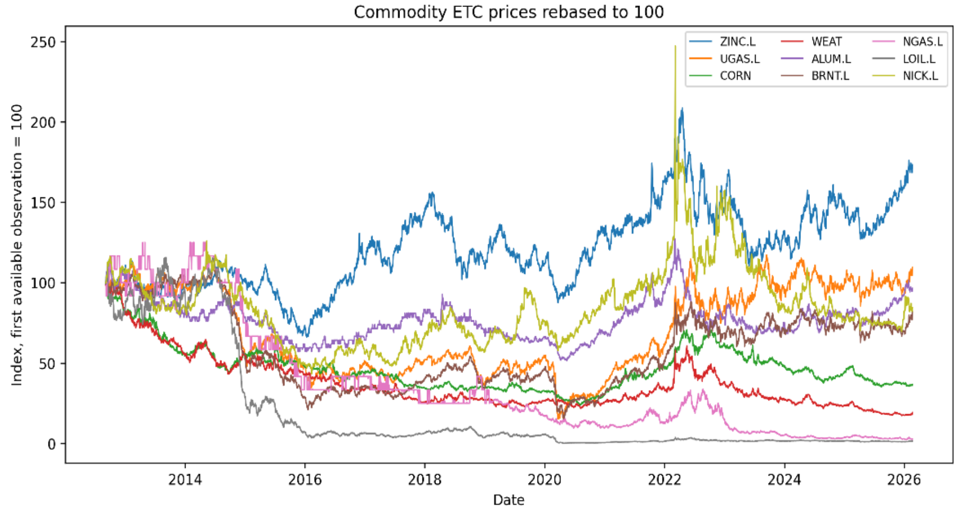

Figure 2. Commodity ETC prices

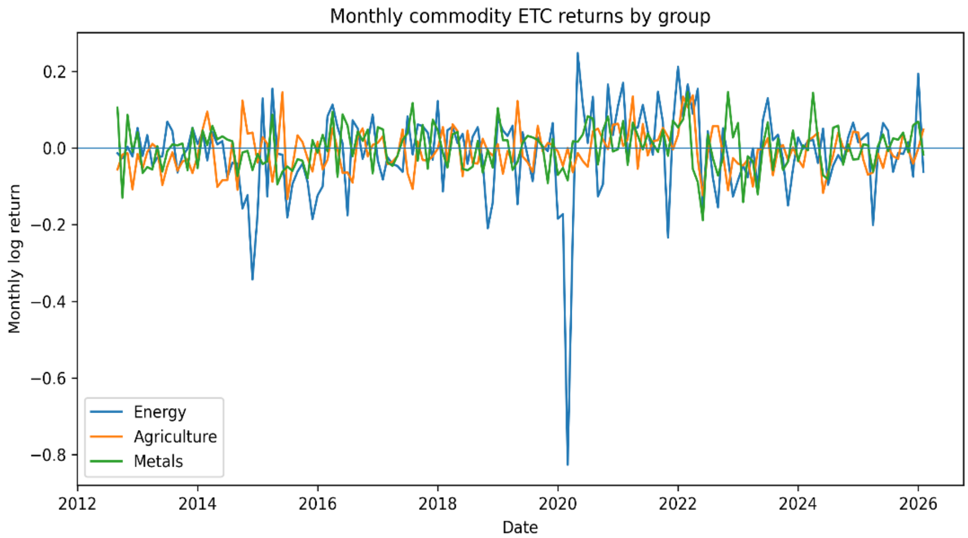

Figure 3. Monthly commodity returns divided by groups

The descriptive evidence in Figures 1–3 highlights three features of the sample. First, month-on-month HICP inflation displays recurrent short-run oscillations and a marked increase in volatility during the 2021–2023 inflationary episode, with the 2022 peak standing clearly outside the range observed in most of the preceding sample. These recurrent fluctuations also suggest that seasonal effects may be relevant and should be considered when interpreting the forecasting results. Second, the rebased ETC price series exhibit substantial long-run heterogeneity. In particular, the performance of futures-based ETCs may reflect not only changes in the corresponding spot commodity prices, but also roll yields, the term structure of futures prices, replication mechanisms and product costs. ETC returns should therefore be interpreted as tradable market-based signals related to commodity conditions rather than as pure measures of spot-price changes. Third, energy returns are considerably more volatile than agricultural and metal returns, especially during the 2020 market disruption and the subsequent energy shock. The stronger empirical role of energy may consequently reflect both its economic pass-through to consumer prices and the greater variation contained in the energy series.

Compared with spot prices, ETCs offer the advantage of being directly tradable financial instruments, reflecting real-time information incorporated by market participants. This forward-looking nature of financial prices makes them particularly suitable for macroeconomic forecasting, as they embed expectations about future economic conditions (Andreou et al., 2013). The dataset includes ETCs representing three broad commodity groups: energy, agriculture, and industrial metals. The sample begins in **September 2012**, which corresponds to the earliest date for which consistent price data are available for all ETCs included in the analysis. The energy group contains ETCs linked to crude oil and natural gas prices. The agricultural group includes ETCs tracking wheat and corn prices, while the industrial metals group includes ETCs linked to aluminium, zinc and nickel prices. Commodity prices are widely recognized as key determinants of inflation dynamics, particularly through the energy channel, which has been shown to be a major source of inflation volatility and forecast errors (Bańbura et al., 2025). Table 1 summarizes the ETCs used in the empirical analysis.

Commodity	**Group**	**ETC Ticker**	**Underlying Commodity**
Energy		LOIL-L	Crude Oil
Energy		UGAS-L	Natural Gas
Energy		BRNT	Brent Crude Oil
Energy		NGAS	Natural Gas
Agriculture		WEAT	Wheat
Agriculture		CORN	Corn
Metals		ALUM-L	Aluminium
Metals		ZINC-L	Zinc
Metals		NICK-L	Nickel

Table 1. Commodity ETCs used in the analysis

Daily log returns are computed for each ETC and used as explanatory variables in the empirical analysis. In order to align the high-frequency commodity data with the monthly inflation series, daily returns are aggregated using the MIDAS framework, which allows the inclusion of multiple daily lags within a monthly regression structure. The full sample spans from **September 2012 to 2025**, providing a sufficiently long time series to estimate the MIDAS models and evaluate their forecasting performance in a nowcasting setting.

4. Methodology

This section describes the econometric framework used to evaluate the relationship between commodity prices and euro area inflation. The analysis proceeds in three steps. First, we estimate a simple baseline regression linking inflation to commodity returns. Second, we implement a MIDAS (Mixed Data Sampling) specification that allows the inclusion of high-frequency financial variables in a monthly inflation model. Finally, we evaluate the predictive performance of the model through a real-time nowcasting exercise and compare it with standard benchmark models.

4.1 Baseline regression

As a first step, we estimate a simple regression model that relates monthly inflation to commodity market developments. The purpose of this baseline specification is to assess whether the different commodity groups display a statistically significant relationship with inflation dynamics.

The baseline model is specified as:

$$\pi_t = \alpha + \beta_1 Energy_t + \beta_2 Agriculture_t + \beta_3 Metals_t + \varepsilon_t$$

where:

- $\pi_t$denotes monthly inflation in the euro area measured by the HICP,
- $Energy_t$, $Agriculture_t$, and $Metals_t$ represent the aggregated returns of the respective commodity groups,
- $\varepsilon_t$is the error term.

This specification provides an initial assessment of the relevance of different commodity sectors in explaining inflation dynamics. The inclusion of commodity prices is motivated by the extensive literature documenting their role as key drivers of inflation, particularly through cost-push channels and energy price pass-through (Bańbura et al., 2025; Hansen et al., 2023).

4.2 MIDAS regression

Because commodity prices are observed at daily frequency while inflation is available monthly, we employ a Mixed Data Sampling (MIDAS) regression framework. MIDAS models allow the direct inclusion of high-frequency variables in regressions explaining lower-frequency macroeconomic variables without requiring the aggregation of the high-frequency data (Ghysels et al., 2004).

In the MIDAS specification, monthly inflation is related to a weighted sum of daily commodity returns observed within the same month. The model can be written as:

$$\pi_t = \alpha + \sum_{k=0}^{K} w(k,\theta)\, r_{t-k}^{HF} + \varepsilon_t$$

where:

- r_{t-k}^{HF}represents daily commodity returns,
- $w(k,\theta)$denotes the weighting function applied to the lags,
- $K$is the number of daily lags included in the regression.

The weights $w(k,\theta)$follow a parametric Beta polynomial structure, which allows the model to summarize a large number of daily observations with only a small number of parameters. This approach preserves the informational content of high-frequency data while maintaining a parsimonious model specification. (Andreou et al., 2013).

MIDAS models have been widely used in macroeconomic forecasting and nowcasting applications, as they provide an effective way to handle mixed-frequency datasets and incorporate timely financial information into macroeconomic models.

4.3 Real-time nowcasting

To evaluate the usefulness of commodity prices for short-term inflation monitoring, we conduct a real-time nowcasting exercise. During each month, forecasts of monthly inflation are updated as new daily commodity price data become available. Nowcasting refers to the prediction of the present or very near future using information available in real time, and it has become a key tool in macroeconomic analysis due to publication delays in official statistics (Knotek and Zaman, 2017; Aliaj et al., 2023).

Specifically, we generate nowcasts of monthly inflation using information available at four different points within the month:

- day 7
- day 14
- day 21
- day 28

This procedure allows us to assess whether high-frequency commodity price movements provide useful information about inflation developments before the official inflation release.

4.4 Benchmark models

To evaluate the predictive performance of the MIDAS model, we compare its forecasting accuracy with two commonly used benchmark models:

- **AR(1) model**

$$\pi_t = \alpha + \phi\pi_{t-1} + \varepsilon_t$$

This model captures the persistence typically observed in inflation dynamics.

- **Random Walk model**

$$\pi_t = \pi_{t-1} + \varepsilon_t$$

The random walk specification represents a simple but often difficult-to-beat benchmark in macroeconomic forecasting (Knotek and Zaman, 2017).

Forecast performance is evaluated using the Root Mean Squared Error (RMSE), which allows a direct comparison of predictive accuracy across models.

5. Empirical Results

This section presents the empirical results of the analysis. We first discuss the baseline regression results linking commodity returns to euro area inflation. We then report the forecasting performance of the MIDAS specification and compare it with simple benchmark models in a nowcasting framework.

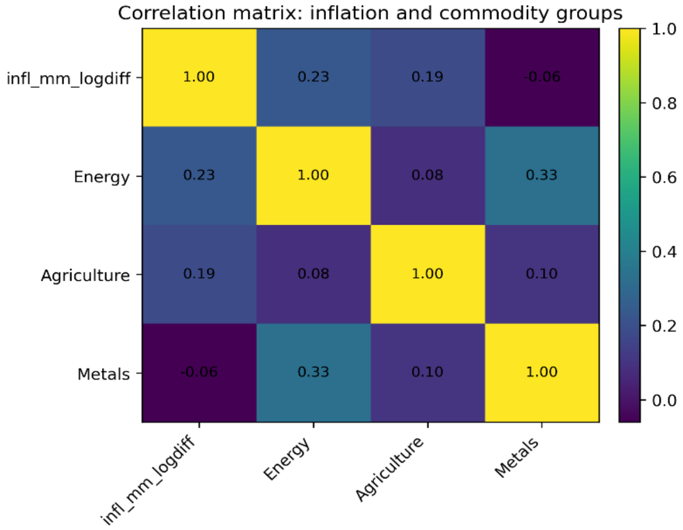

Figure 4. Correlation matrix among the inflation and the commodity groups

Figure 4 provides preliminary evidence of a positive but moderate contemporaneous association between inflation and energy returns (0.23). Agricultural returns display a slightly weaker positive correlation with inflation (0.19), whereas the correlation with industrial metals is close to zero and negative (−0.06). The positive correlation between energy and metal returns (0.33) may reflect their common exposure to global demand conditions and industrial activity. Overall, the unconditional correlations suggest that commodity returns contain some information about inflation, but the relationships are not sufficiently strong to imply substantial forecasting power on their own.

5.1 Baseline regression results

We begin by estimating the baseline regression that relates monthly inflation to returns of the three commodity groups: energy, agriculture and metals. The results indicate that energy commodity returns display a positive and statistically significant relationship with euro area inflation, suggesting that developments in energy markets are an important driver of inflation dynamics. This finding is consistent with the large literature documenting the strong pass-through from energy prices to consumer prices (Bańbura et al., 2025; López et al., 2024). In contrast, the coefficient associated with agricultural commodities appears weaker and only marginally significant, while industrial metals do not exhibit a statistically significant relationship with inflation. These results suggest that, within the sample considered, energy markets provide the strongest signal about inflation developments. Overall, the baseline regression explains a modest fraction of inflation variability, with an R^2 of approximately 0.11, indicating that while commodity prices contain useful information, they capture only a limited share of the overall dynamics of euro area inflation.

5.2 MIDAS nowcasting results

We next evaluate whether high-frequency commodity returns improve short-term inflation monitoring using a MIDAS regression framework. To assess the timing of information arrival during the month, we generate nowcasts of monthly inflation at four different points within the month: day 7, day 14, day 21 and day 28. Forecast accuracy is evaluated using the Root Mean Squared Error (RMSE).

The results are reported below:

Nowcast timing	**RMSE**
Day 7	0.00410
Day 14	0.00423
Day 21	0.00444
Day 28	0.00462

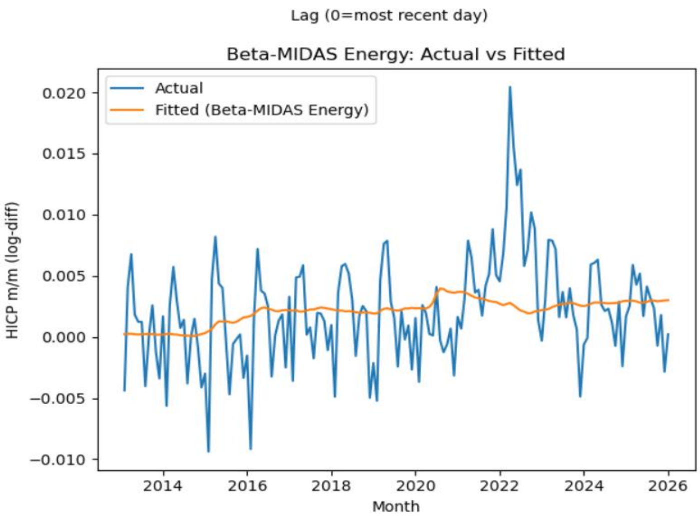

Figure 5. Energy Beta-MIDAS: actual and fitted inflation

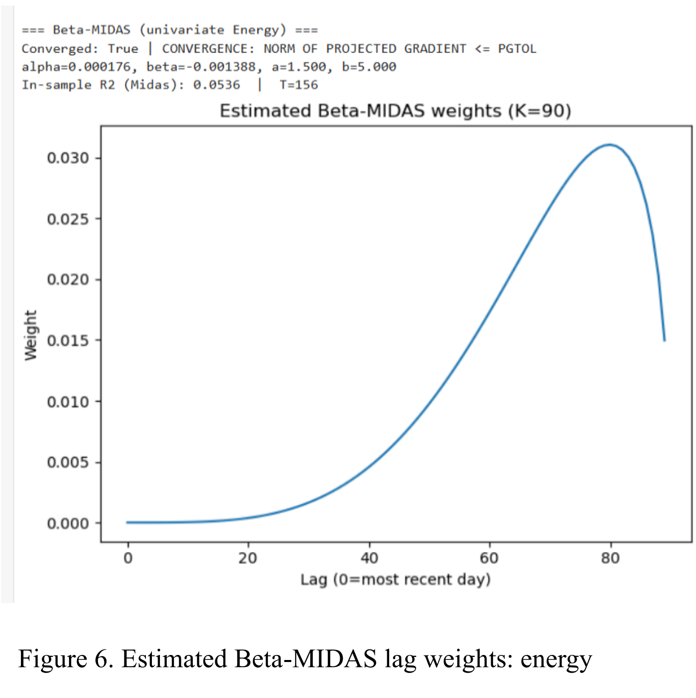

Figure 6. Estimated Beta-MIDAS lag weights: energy

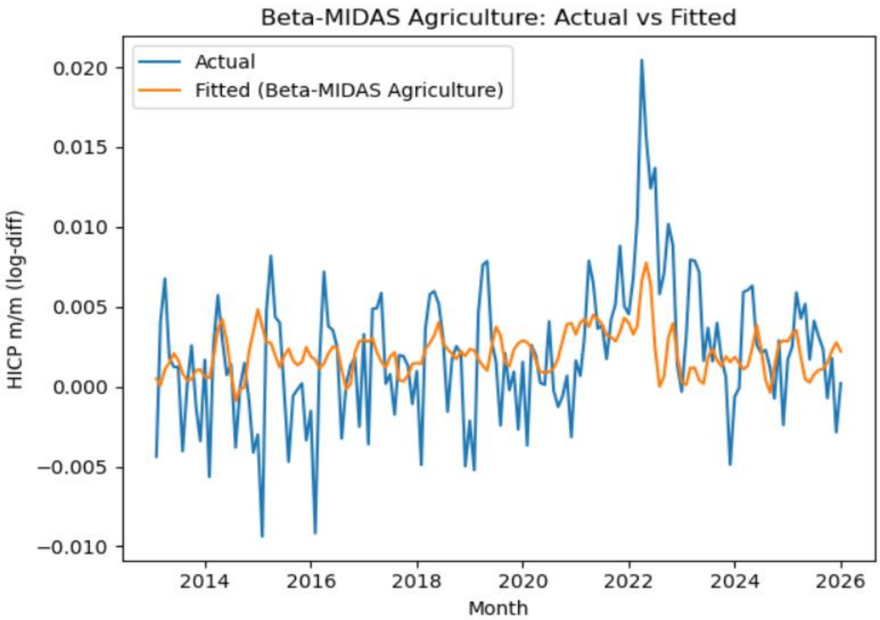

Figure 7. Agriculture Beta-MIDAS: actual and fitted inflation

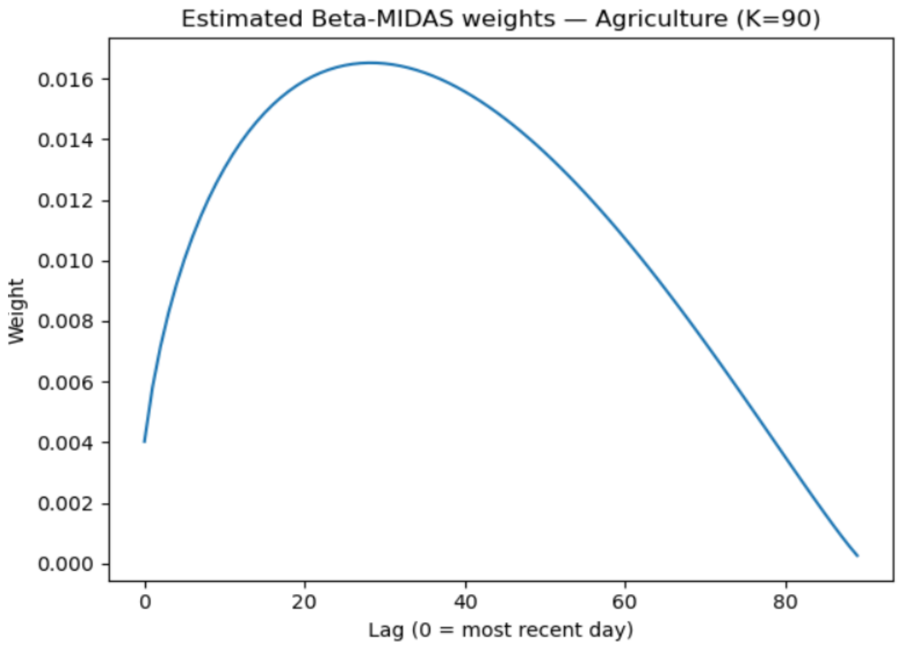

Figure 8. Estimated Beta-MIDAS lag weights: agriculture

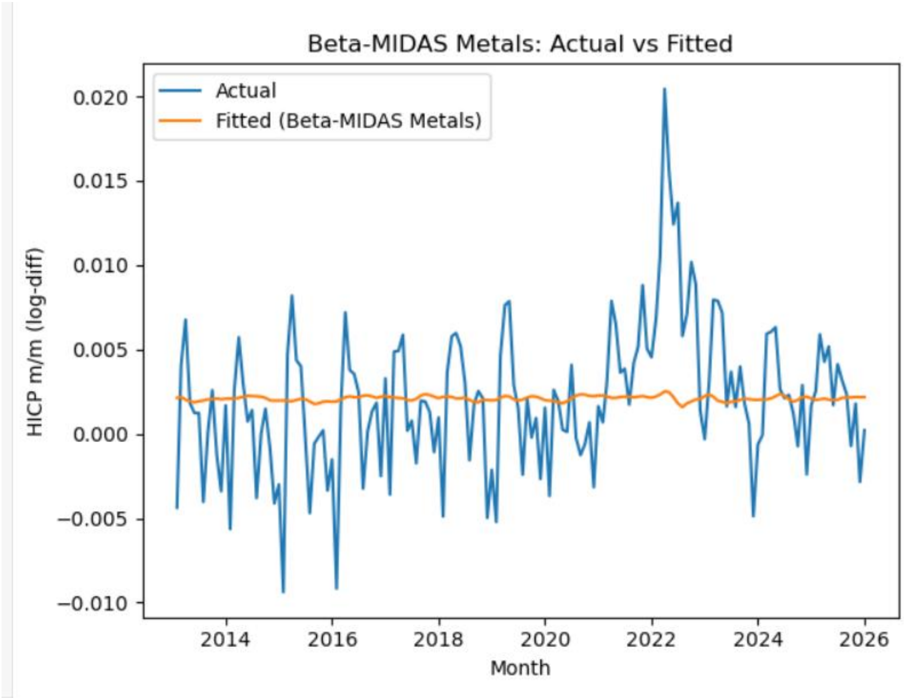

Figure 9. Metals Beta-MIDAS: actual and fitted inflation

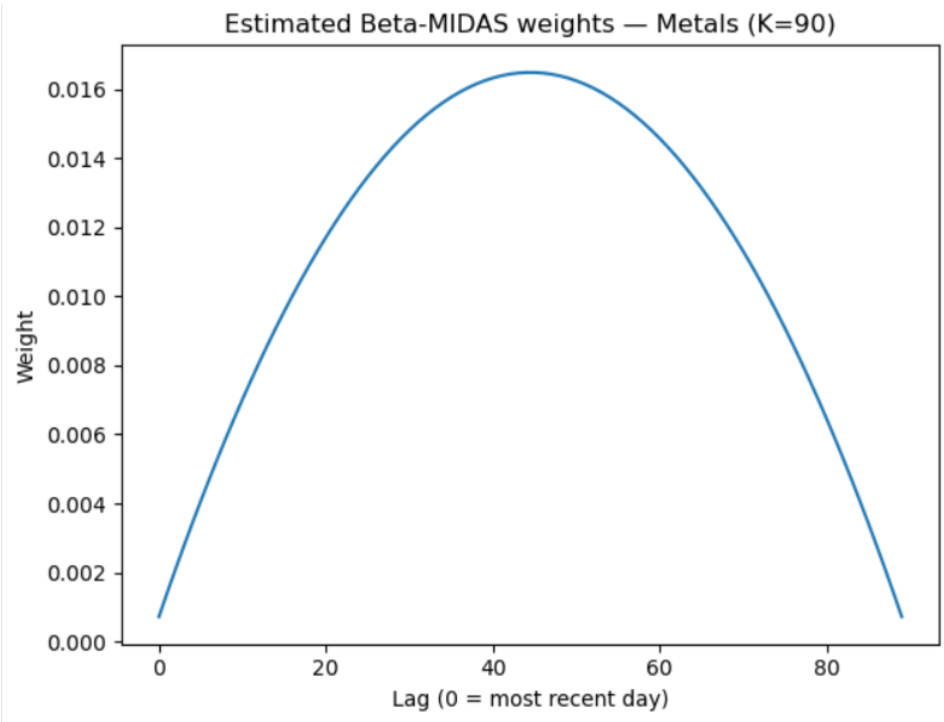

Figure 10. Estimated Beta-MIDAS lag weights: industrial metals

Figures 5–10 provide additional evidence on both model fit and the timing of the commodity–inflation relationship. The fitted series are substantially smoother than actual month-on-month inflation and fail to reproduce most short-lived fluctuations, particularly the magnitude of the 2021–2023 inflation surge. The energy and agriculture specifications display some response to the post-pandemic increase in inflation, whereas the fitted values obtained from industrial metals remain nearly constant. The estimated weighting functions also reveal heterogeneous transmission lags. Energy receives its largest weights toward the more distant part of the 90-day window, at approximately 75–80 trading-day lags, which is consistent with a delayed pass-through through production, transportation and retail-pricing channels. Agricultural returns receive their largest weights at approximately 25–30 days, while the metal specification has a broad hump centred around 40–50 days. The models therefore do not indicate that the most recent daily observations are necessarily the most informative; rather, commodity-price movements appear to affect inflation with sector-specific delays.

The multivariate Beta-MIDAS model records its lowest forecasting error at day 7, with an RMSE of 0.00410. The error then increases monotonically, reaching 0.00462 at day 28. Under the current specification, therefore, the observations added later in the month do not improve forecast accuracy. This finding should not be interpreted as definitive evidence that early-month returns are intrinsically more informative: the deterioration may instead reflect short-term commodity-market noise, delayed pass-through to consumer prices, or sensitivity to the specification of the real-time information set. Overall, extracting a stable forecasting signal from high-frequency commodity returns remains challenging.

=== Real-time nowcasting evaluation (Energy Beta-MIDAS) ===

	day	RMSE	MAE	N
0	7	0.004345	0.003251	96
1	14	0.004470	0.003301	96
2	21	0.004591	0.003364	96
3	28	0.004665	0.003417	96

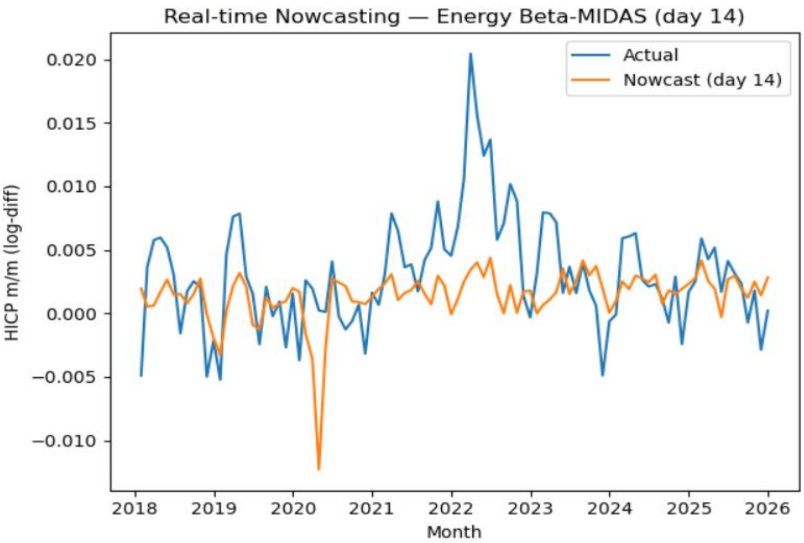

Figure 11. Univariate Energy Beta-MIDAS real-time nowcast (day 14)

Figure 11 illustrates a further limitation of relying on energy-market returns in isolation. During the 2020 market disruption, the univariate energy model generates an exceptionally large negative nowcast that is not matched by the observed decline in HICP inflation. This episode suggests that extreme movements in futures-based ETCs may reflect temporary financial-market dislocations that do not pass through proportionally or immediately to consumer prices. The result is consistent with the need to distinguish transitory market stress from persistent inflationary pressures.

5.3 Comparison with benchmark models

To better evaluate the forecasting performance of the MIDAS specification, we compare it with two standard benchmark models: an autoregressive AR(1) model and a random walk specification.

The forecasting performance of the different models is summarized below.

Nowcast day	**RMSE**	**MAE**	**N**
7	0.004101	0.003149	96
14	0.004229	0.003265	96
21	0.004440	0.003385	96
28	0.004617	0.003473	96

Table 2. Real-time forecasting performance of the multivariate Beta-MIDAS model

Model	**RMSE**	**MAE**	**N**
AR1	0.003572	0.002762	99
RW	0.003587	0.002861	99
CIdx	0.004655	0.003389	99

Table 3. Out-of-sample forecasting performance of the benchmark models

Model	**RMSE**	**MAE**	**N**
AR1	0.003572	0.002762	99
RW	0.003587	0.002861	99
MV-BetaMIDAS (day 28)	**0.004617**	**0.003473**	**96**
CIdx	0.004655	0.003389	99

Table 4. Day-28 multivariate Beta-MIDAS and benchmark comparison

Note: the multivariate Beta-MIDAS evaluation contains 96 observations, whereas the benchmark and commodity-index evaluations contain 99. The reported comparison is therefore descriptive and should be supplemented by a robustness comparison computed over the common forecast sample.

Subject to this sample-comparability limitation, the performance gap is economically meaningful: the day-28 multivariate Beta-MIDAS RMSE is approximately 22.6% higher than the AR(1) RMSE and 22.3% higher than the random-walk RMSE. The comparison with the commodity-index benchmark is more nuanced. The MIDAS model records a marginally lower RMSE but a higher MAE, indicating that the ranking depends on the relative importance assigned to large forecast errors. By contrast, the autoregressive benchmarks perform better under both loss measures.

The results indicate that **simple benchmark models outperform the MIDAS specification in terms of forecasting accuracy**. In particular, the AR(1) model delivers the lowest forecasting error, closely followed by the random walk model. This result highlights the well-known difficulty of improving upon simple autoregressive models when forecasting inflation (Knotek and Zaman, 2017). While commodity prices contain economically meaningful information, particularly through the energy channel (Hansen et al., 2023), their inclusion does not translate into improved out-of-sample forecasting performance in this specification. Taken together, the results suggest that commodity prices, especially energy prices, are significantly related to inflation dynamics in the euro area. However, exploiting this information for forecasting purposes proves more challenging. One possible explanation is that inflation exhibits strong persistence, which allows simple autoregressive models to perform well in forecasting exercises. Additionally, commodity prices may introduce substantial short-term volatility that does not always translate into sustained changes in consumer prices. These findings indicate that while financial commodity markets provide useful signals about inflation pressures, incorporating this information into forecasting models requires careful specification and may benefit from richer model structures or additional explanatory variables.

6. Conclusion

This paper examines whether high-frequency commodity market information can improve the nowcasting of euro area inflation. Specifically, we investigate whether daily returns of exchange-traded commodity products (ETCs) can provide useful signals for predicting monthly inflation measured by the Harmonised Index of Consumer Prices (HICP). The analysis combines monthly inflation data with daily financial market data for commodities in three major sectors: energy, agriculture, and industrial metals. To address the mixed-frequency nature of the data, we employ a MIDAS (Mixed Data Sampling) regression framework, which allows the inclusion of high-frequency financial variables in a model explaining lower-frequency macroeconomic outcomes (Ghysels et al., 2004). In addition to the MIDAS specification, we estimate a baseline regression and evaluate forecasting performance through a real-time nowcasting exercise conducted at several points within the month. The empirical results highlight several important findings. First, energy commodity returns display a positive and statistically significant relationship with euro area inflation. This result is consistent with the well-documented importance of energy prices in driving inflation dynamics through both direct and indirect channels (Bańbura et al., 2025; López et al., 2024). In contrast, agricultural commodities show weaker statistical significance, while industrial metals do not appear to play a major role in explaining inflation fluctuations in the sample considered. Second, the nowcasting exercise shows that the lowest MIDAS forecast error is obtained at day 7, while accuracy deteriorates as later observations are added. In conjunction with the estimated lag weights, this pattern suggests that commodity information may operate through delayed sector-specific transmission rather than immediate within-month updates. However, the overall forecasting performance of the MIDAS specification remains limited when compared with simple benchmark models. In particular, the AR(1) and random walk models outperform the MIDAS specification in terms of out-of-sample forecasting accuracy. This result highlights a well-known feature of inflation dynamics: the strong persistence of inflation often makes simple models difficult to beat in forecasting exercises (Knotek and Zaman, 2017). Overall, the findings suggest that commodity markets do contain relevant information about inflation developments in the euro area, particularly through the energy channel. However, translating this information into improved forecasting performance is not straightforward. This reflects both the noisy nature of high-frequency financial data and the complexity of the transmission mechanisms linking commodity prices to consumer prices. These results open several avenues for future research. First, richer model specifications could be explored, including the combination of commodity prices with additional high-frequency financial indicators or macroeconomic variables. Second, alternative econometric approaches—such as factor models or machine learning techniques—may help extract more informative signals from high-frequency datasets (Aliaj et al., 2023). Finally, further work could investigate the role of structural changes in energy markets and global supply chains in shaping the relationship between commodity prices and inflation, particularly in the context of recent economic shocks (Hansen et al., 2023).

References

Aliaj, T., Ciganovic, M., & Tancioni, M. (2023). *Nowcasting inflation with Lasso-regularized vector autoregressions and mixed frequency data*. Journal of Forecasting, 42(3), 464–480.

Andreou, E., Ghysels, E., & Kourtellos, A. (2013). *Should macroeconomic forecasters use daily financial data and how?* Journal of Business & Economic Statistics, 31(2), 240–251.

Armesto, M. T., Engemann, K. M., & Owyang, M. T. (2010). *Forecasting with Mixed Frequencies*. Federal Reserve Bank of St. Louis Review, 92(6), 521–536.

Asgharian, H., Hou, A. J., & Javed, F. (2013). *The Importance of the Macroeconomic Variables in Forecasting Stock Return Variance: A GARCH-MIDAS Approach*. Journal of Forecasting, 32(7), 600–612.

Baba, C., & Lee, J. (2022). *Second-Round Effects of Oil Price Shocks: Implications for Europe's Inflation Outlook*. IMF Working Paper No. 22/173.

Bańbura, M., Giannone, D., Modugno, M., & Reichlin, L. (2013). *Now-Casting and the Real-Time Data Flow*. In G. Elliott & A. Timmermann (Eds.), Handbook of Economic Forecasting (Vol. 2).

Bańbura, M., Bobeica, E., Giammaria, A., Porqueddu, M., & van Spronsen, J. (2025). *A New Model to Forecast Energy Inflation in the Euro Area*. ECB Working Paper No. 3062.

Baumeister, C. (2023). *Pandemic, War, Inflation: Oil Markets at a Crossroads?* ECB Forum on Central Banking.

Beck, G. W., Carstensen, K., Menz, J.-O., Schnorrenberger, R., & Wieland, E. (2024). *Nowcasting Consumer Price Inflation Using High-Frequency Scanner Data: Evidence from Germany*. ECB Working Paper No. 2930.

Ferrucci, G., Jiménez-Rodríguez, R., & Onorante, L. (2010). *Food Price Pass-Through in the Euro Area: The Role of Asymmetries and Non-Linearities*. ECB Working Paper No. 1168.

Foroni, C., Marcellino, M., & Schumacher, C. (2011). *U-MIDAS: MIDAS Regressions with Unrestricted Lag Polynomials*. Deutsche Bundesbank Discussion Paper No. 35/2011.

Foroni, C., Marcellino, M., & Stevanović, D. (2018). *Mixed Frequency Models with MA Components*. ECB Working Paper No. 2206.

Ghysels, E., Santa-Clara, P., & Valkanov, R. (2004). *The MIDAS Touch: Mixed Data Sampling Regression Models*.

Gorton, G., & Rouwenhorst, K. G. (2006). *Facts and Fantasies About Commodity Futures*. Financial Analysts Journal, 62(2), 47–68.

Hamilton, J. D., & Wu, J. C. (2014). *Effects of Index-Fund Investing on Commodity Futures Prices*. NBER Working Paper No. 19892.

Hansen, N.-J., Toscani, F., & Zhou, J. (2023). *Euro Area Inflation after the Pandemic and Energy Shock: Import Prices, Profits and Wages*. IMF Working Paper No. 131.

Huber, F., Onorante, L., & Pfarrhofer, M. (2022). *Forecasting Euro Area Inflation Using a Large Panel of Survey Expectations*.

Knotek, E. S., & Zaman, S. (2017). *Nowcasting U.S. Headline and Core Inflation*. Journal of Money, Credit and Banking, 49(5), 931–968.

Libonatti, L. (2020). *MIDAS Modeling for Core Inflation Forecasting*. Journal of Regional Research, 245–283.

Linzenich, J., & Meunier, B. (2025). *Nowcasting Made Easier: A Toolbox for Economists*. ECB Working Paper No. 3004.

López, L., Odendahl, F., Párraga, S., & Silgado-Gómez, E. (2024). *The Pass-Through to Inflation of Gas Price Shocks*. ECB Working Paper No. 2968.

Modugno, M. (2011). *Nowcasting Inflation Using High Frequency Data*. ECB Working Paper No. 1324.

Neri, S., et al. (2023). *Energy Price Shocks and Inflation in the Euro Area*. SUERF Policy Brief.