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On the predictive power of food commodity futures prices in forecasting inflation

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Within the context of forecasting U.S. inflation, this study explores the predictive power of food commodities futures prices, focusing on enhancing the precision of both short- and long-term forecasts. We develop single commodity models for twelve different food commodities and also construct two aggregated models: a simple component model and a Principal Component Analysis (PCA)-based model, both utilizing price indices of the selected commodities. Monthly futures data from 1996 to 2023 for the nearest maturity dates are segmented into in-sample fitting and out-of-sample forecasting, covering forecast horizons of 3, 6, 9 and 12 months. Our findings indicate that aggregated models, particularly the PCA-based method, exhibit superior forecasting performance. Furthermore, to verify model robustness, we conduct parallel forecasts using spot prices and perform subsample analyses. Collectively, these results underscore the predictive power of commodity futures for forecasting food inflation.

Keywords: Food commodities; inflation forecasting; futures prices; commodity markets

1. Introduction

As a key indicator of economic vitality, the inflation rate plays a crucial role in economic decision-making and policy formulation (Yu *et al.* 2024). In a globalized economic system, food price volatility attracts particular attention due to its direct impact on consumers' cost of living and global food security (Grunberg 1998). Notably, futures prices of food commodities, reflecting the market expectations of future food price trends, are essential in understanding and forecasting inflation dynamics. Although traditional macroeconomic models are extensively employed in predicting inflation, the role and effectiveness of information from futures markets for food commodities in such forecasts remain a topic of ongoing investigation.

In recent years, the increasing complexity of the global food supply chain and the growing influence of climate change on agricultural production have contributed to increased food price volatility (Haile *et al.* 2017). Such volatility not only reflects immediate fluctuations in supply and demand but also captures the market participants' expectations about future trends. For this reason, futures prices of food commodities have emerged as a valuable information source, offering insights important in forecasting both short-term and long-term inflation trends (Ball *et al.* 1990). Moreover, given the significant proportion that food prices constitute within the Consumer Price Index (CPI), the changes in food futures prices can directly influence the measurement and prediction of inflation rates (Stock and Watson 2003).

On the other hand, the commodity futures market, serving as a forward-looking indicator that reflects anticipations of future commodity prices, provides a unique perspective for monitoring and predicting inflationary trends. These markets aggregate information from around the globe, including expectations about weather patterns, crop yields, and shifts in trade policies, all critical factors that influence food prices (Stock and Watson 1999). Therefore, understanding and utilizing the dynamics of commodity futures prices could provide critical insights for forecasting inflation. There is also research employing econometric models that consider the intrinsic characteristics of market prices themselves, such as persistence, endogeneity, and conditional heteroskedasticity

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effect, to explore the indirect effects of food price volatility on inflation (Granger 1969, Engle 1982).

Our present study is dedicated to examining how futures prices of food commodities can improve forecasting food and headline inflation. Incorporating futures and spot prices of twelve food commodities along with one indicator of economic activity, we adopt the methodological framework from Tule *et al.* (2019). Distinguishing our approach from Tule *et al.* (2019), we enhance the model by incorporating futures prices across various maturities, leveraging their forward-looking nature. By integrating the information embedded in these prices, our approach aims to deliver improved forecast accuracy.

The remainder of this paper is structured as follows: Section 2 comprises a literature review, theoretical motivations, and an outline. Section 3 delineates the research methodology. Section 4 describes the data and presents some preliminary analyses and pre-testing results. Section 5 discusses the findings of the empirical analysis. Section 6 concludes the paper.

2. Literature review

2.1. Forecast inflation

Accurate inflation forecasting is essential for guiding economic and financial decision-making. Inflation impacts the purchasing power of individuals and businesses, rendering forecasts of futures price levels a crucial determinant of saving and investment behaviors (Friedman 1977). In the realm of monetary policy, central banks rely upon inflation forecasts to set interest rates, with the aim of achieving price stability and objectives of economic growth (Mishkin 2004). Within financial markets, investors utilize inflation predictions to assess the future value and risk of assets, highlighting the impact of forecasting precision on market efficiency. Inflation uncertainty is perceived as inhibiting economic decision-making and growth; high-quality inflation forecasts can diminish such uncertainties and bolster market confidence. The literature on inflation forecasting is extensive. Monetary authorities and analysts continually strive for accurate inflation predictions, a drive that also fosters the ongoing refinement and enhancement of existing models to achieve more precise and reliable forecasts. With the deepening of research, models used for predicting inflation evolved from time-series analyses to more sophisticated multivariate econometric models. Early forecasting tools, such as the univariate autoregressive (AR) models (Nelson 1972), progressed. The introduction of vector autoregressive (VAR) models enhanced the accuracy of predictions (Sims 1980). With technological advancements, researchers began to employ more advanced techniques, like dynamic stochastic general equilibrium (DSGE) models, which encompass a profound understanding of economic structures and could capture the impact of macroeconomic policy shifts on inflation (Smets and Wouters 2007). Moreover, the identification of structural breaks and heteroskedasticity played a key role in improving the accuracy of inflation forecasts, especially in the face of economic crises or major policy shifts (Stock and Watson 2007). Recent studies further explored the application of machine learning methods in inflation forecasting, with such approaches being particularly adept at handling large-scale datasets and identifying nonlinear patterns. For instance, artificial neural networks and support vector machines have been employed in predicting the spot prices of food commodities, exhibiting superior predictive performances over traditional time-series methods (Kumar and Thenmozhi 2006). However, the complexity of these methods necessitates high-quality data and expertize to ensure the accuracy of the models.

2.2. Food commodities

As a key component of the Consumer Price Index (CPI), food commodity prices are directly reflected in inflation metrics (Gilbert and Morgan 2010). Economists have identified a significant positive correlation between food prices and inflation, with a more pronounced effect on the CPI in lower-income nations (Ivanic and Martin 2008). This phenomenon could be largely attributed to the substantial proportion of food expenditure in the consumption patterns of low-income households, wherein increases in food prices swiftly translate into overall inflation rates (Raue *et al.* 2009). Beyond these direct effects, food price volatility is also closely linked to the supply-demand dynamics of agricultural commodity markets, production costs, trade policies, and international market prices (Gilbert 2010). Thus, the precision of food price fluctuation forecasts depends not only on the comprehension of these foundational factors but also on the analysis of correlated macroeconomic variables such as exchange rates, energy prices, and monetary policies (Piesse and Thirtle 2009). Certain studies, such as Merritt (2012), incorporated the forecasting of food prices into inflation prediction models, taking into account a variety of predictive variables, including futures market information and seasonal factors. Policymakers exhibit particular interest in the accurate forecasting of food inflation due to its implications for social welfare and economic stability. Precise predictions of food inflation enable central banks to implement timely monetary policy measures aimed at mitigating the impact of food price volatility on the economy and protecting the most vulnerable groups from the adverse effects of price fluctuations (Baffes and Haniotis 2010). On the other hand, the complexity of food price forecasting has led to continued debates over model selection and risk assessment, especially in the context of extreme weather events and global supply chain disruptions (Deaton and Laroque 1992, Gilbert and Morgan 2010). Ultimately, these research efforts underscore the critical role of food price volatility forecasting in food security, agricultural policy, and the stability of global markets while also furnishing economists and decision-makers with invaluable insights to formulate more effective response strategies and mitigation solutions (Timmer 2010).

2.3. Forecast in specific commodities

The predictability of futures commodity prices constitutes a central theme within the ambit of financial economics

research. Studies indicated that despite the oft-debated efficiency properties of futures markets, the predictability of futures prices indeed prevails under certain conditions. Gorton and Rouwenhorst (2006) argued in their work that the risk premia of commodity futures could be predicted through time-series models, which correlate with commodities' storage costs and convenience yields. Furthermore, Singleton (2014) underscored the significance of comprehending the nuances of micro-market structures and participant behaviors for the prognostication of futures prices. He posited that the heterogeneity in beliefs and risk preferences of traders plays an important role in the price formation process. Regarding individual commodities, Litzenberger and Rabinowitz (1995) demonstrated the predictability of futures prices by modeling commodity supply and demand fluctuations. They discovered that, by taking into account the cyclical variations of harvest cycles and consumption patterns, it is possible to forecast the futures prices of certain agricultural products with relative accuracy. Similarly, the study by Fama and French (1988) indicated that the theory of storage costs could be employed to explain the pricing trends of metal futures. The situation with multiple commodities is decidedly more complex, as prices might be influenced by cross-commodity supply and demand shocks as well as fluctuations in risk preferences. Tang and Xiong (2012) highlighted that cross-commodity risk premia and the needs of market participants for risk management are crucial to comprehending the behaviors of futures prices across various commodities. Their model took into account how traders allocate risk among different commodities and demonstrated how these dynamics are reflected in pricing.

Although these studies furnished evidence for the predictability of commodity futures prices, they also unveiled the limitations inherent in forecasting. Schwartz and Smith (2000) deliberated upon the practical application of predictive models, noting that despite instances of success, the imperfect information of markets and random shocks frequently culminate in predictive discrepancies. This suggests that for investors and policymakers seeking to hedge risks through futures markets, grasping the significance of microeconomic factors is as paramount as understanding macroeconomic conditions.

2.4. Salient features of commodity prices

The volatility of commodity prices in future markets has long been a salient research topic within the discipline of financial economics. Price persistence reflects the temporal propagation characteristics of price volatility, which is particularly pronounced in futures markets. This is because price fluctuations are driven not only by fundamental supply and demand relations but are also influenced by expectations of market participants and strategic behaviors (Pindyck 2001). The issue of endogeneity is especially prominent in futures markets, as the anticipations of the market and the strategic decisions of investors interact, forming the dynamics of price movements (Hamilton and Susmel 1994). Moreover, the conditional heteroskedasticity of futures prices refers to the non-constant nature of market volatility over time, which is typically captured by models such as Autoregressive Conditional Heteroskedasticity (ARCH) and Generalized Autoregressive Conditional Heteroskedasticity (GARCH) (Bollerslev 1986).

In light of the growing recognition of the significance of microstructural elements, particularly in terms of how market microstructures affect macroeconomic price volatility, the inherent statistical challenges presented by the endogeneity of trading activities and the price discovery mechanisms of futures markets have become central to the development of modeling strategies. Against this backdrop, Engle and Rangel (2008) introduced an innovative approach to modeling heteroskedasticity that accounts for price persistence and potential structural breaks. In summary, the volatility of futures commodity prices is not solely a reflection of macroeconomic factors but rather a confluence of market endogenous forces and the characteristics of microstructural features. A thorough investigation of persistence, endogeneity, and conditional heteroskedasticity provides a critical foundation for understanding and forecasting the dynamics of futures prices.

2.5. Theoretical motivation

In summary, in the global economy, the volatility of food prices profoundly impacts consumer welfare and economic stability. Particularly for developing and low-income nations, the instability of food prices significantly influences the cost of living and food security for residents. In recent years, the instability of food prices has been further exacerbated by extreme weather events, geopolitical tensions, uncertainties in global trade policies, and fluctuations in other macroeconomic factors. This volatility affects not only consumers and producers but also poses challenges to policymakers in formulating monetary policies and food security strategies. Therefore, improving the accuracy of inflation forecasts is crucial for reducing uncertainty surrounding inflation and devising effective macroeconomic policies.

Numerous scholars in the literature have endeavored to enhance models and methodologies for inflation forecasting to improve predictive accuracy. These efforts span from traditional time series models, such as VAR models, to more recent applications of machine learning and deep learning techniques, including random forests and support vector machines. While these methods have indeed contributed to greater flexibility and accuracy in forecasting, they also bring forth varying levels of unresolved challenges. Upon preliminary investigation, we discovered that the proposed econometric model demonstrated superior predictive performance. In our future studies, we aim to enhance the performance of machine learning models through careful parameter tuning and methodological improvements to forecast inflation.

Despite the growing diversity of inflation forecasting approaches, accurately predicting future inflation remains a complex task. This study primarily references widely used models, such as the Phillips curve (e.g. Mankiw 1994, Section 11.2), to construct a relatively stable linear model, aiming to predict food inflation by exploring the interconnections among 12 food commodities and the civilian unemployment rate. The motivation behind this investigation is to leverage the latent predictive capacity of commodity futures

prices and to utilize this to build a robust inflation forecasting model, facilitating both short- and potentially long-term projections. Additionally, this paper conducts a comparative analysis with spot prices, examining the complexities within the food commodity market and assessing whether these market characteristics consistently influence inflation rate predictions. Through an in-depth exploration of the predictability of food commodity futures prices, this study aspires to provide a more precise tool for inflation forecasting, thereby enabling stakeholders to respond more effectively to fluctuations in price dynamics.

2.6. Outline and contribution

We reference various linear models to evaluate predictive effectiveness and refine the baseline model constructed by Tule *et al.* (2019), which serves as our benchmark model. Our primary focus is assessing the predictability of U.S. futures prices for twelve distinct food commodities. Prior to empirical testing, we employ several approaches to construct food price indices. The first approach involves developing a forecast component aimed at preserving the original price trends of the twelve commodity futures. The second approach utilizes principal component analysis (PCA) to construct a composite price index. This method yields an index derived fundamentally from the principal components extracted through PCA, encompassing the pricing characteristics of the selected twelve food items and addressing multicollinearity issues within the same regression model. The third approach employs inflation forecasting based on individual commodities, aimed at determining the predictive capacity of a single commodity. These three methods are applied for in-sample model training and out-of-sample forecasting. To evaluate the predictive performance of the constructed model, we incorporated spot prices as a robustness check. Spot prices are generally considered a dataset more effectively capturing inflation trends, given their reliance on current market data.

This study offers two principal contributions. First, it conducts an examination of the model's applicability across various data contexts. Presently, reliance often leans toward spot price data due to its provision of more immediate and accurate market information. However, futures prices include market expectations regarding futures price uncertainties. In addition, the futures market is much more liquid than the spot market, which is often vaguely defined. Our primary focus is, therefore, on futures prices, specifically selecting the contract prices nearest to expiration in the market. The resulting forecasts are then compared with spot prices to validate the model's predictive accuracy. Secondly, we develop a more stable model structure. Drawing on Tule *et al.* (2019)'s analysis of the persistent characteristics of food prices, we incorporate differencing components and include lagged inflation as an explanatory variable to enhance the model's robustness. Different methodologies are employed to construct food commodity indices, including a simple component method and a PCA-based method. Our study leverages the constructed indices to evaluate the model's capacity for inflation forecasting.

3. Methodology

We start by presenting our forecasting models, including component models with the sum of different commodities' futures prices and single commodity models with single commodity futures prices in each. These models extend the expectations augmented Phillips curve by incorporating commodity futures prices as additional explanatory variables (Mankiw 1994, Section 11.2). The rationale for this extension is that commodity futures prices reflect market expectations of future commodity prices, which can help to forecast inflation. After that, we will state our forecasting procedure, which is based on the estimation of the models above.

3.1. Models

First, we construct the simple component model, which includes each individual commodity as an explanatory variable. Next, we apply principal component analysis to develop the principal component model. Following this, we introduce the single commodity models and the corresponding benchmark models for component and single commodity models.

3.1.1. Simple component model. We select twelve commodity prices along with an economic activity indicator (civilian unemployment rate) to construct the linear model:

$$H_S \ : \ \pi_{t+h} = \phi\pi_t + \sum_{i=1}^{12} \psi_{i,x}(x_{i,t} - \rho_{i,x}x_{i,t-1}) + \psi_z(z_t - \rho_z z_{t-1}) + \varepsilon_{\pi,t}, \quad h = 3, 6, 9, 12, \quad (1)$$

where π_t denotes monthly inflation at time t calculated by $\log(\text{CPI}_t/\text{CPI}_{t-1})$, $x_{i,t}$ denotes the differenced price of ith food commodity futures contract at time t ($i = 1, \ldots, 12$), and h can be 3, 6, 9 or 12 months. z_t is economic activity. While ρ is the first-order autocorrelation coefficient, where the inclusion of the terms $x_{i,t} - \rho_{i,x}x_{i,t-1}$, for instance, is meant to capture any potential persistence effect in the predictive model, and the endogeneity effect is subsumed in ψ.† This approach retains all twelve food prices in the forecasting combination, allowing for the preservation of the full spectrum of price information.

The above model resembles an Error Correction Model (hereafter ECM, see, for example, Engle and Granger (1987)) in that it includes autoregressive information π_t and lagged stationary explanatory variables to capture short-term dynamics by terms like $x_{i,t} - \rho_{i,x}x_{i,t-1}$ (note that here x is the differenced futures prices). However, unlike a traditional ECM, we do not include an explicit error correction term of the form $\pi_t - \beta x_{i,t}$ to capture the long-term dynamics. The key reason is that the futures-based variables in our model are forward-looking by nature and are already differenced and stationary according to table 3. Including an error correction term such

† Tule *et al.* (2019)'s analysis revealed that the predictive sequence exhibits several notable characteristics, such as persistence, endogeneity, and conditional heteroskedasticity (high volatility) effects.

as $\pi_t - \beta x_{i,t}$ would imply that current inflation π_t adjusts toward a level implied by a forward-looking predictor $x_{i,t}$, which conflicts with the logic of our forecasting framework.

Our estimation is a two-step procedure. In the first step, we estimate autoregressive processes for the stationary predictors:

$$x_{i,t} = \rho_{i,x} x_{i,t-1} + v^x_{i,t}, \quad z_t = \rho_z z_{t-1} + v^z_t. \tag{2}$$

Here we do not incorporate a constant term in the first-step regression because taking first order difference for non-stationary prices has already removed the constant across time. Furthermore, we also subject this theory to empirical testing and found that the constant term was not statistically significant in the regression. The predictive results further indicate that the model without the constant term outperforms the one with it in terms of forecasting accuracy. Next, we regress future inflation π_{t+h} on π_t, and the stationary residual terms $x_{i,t} - \rho_{i,x} x_{i,t-1}$ and $z_t - \rho_z z_{t-1}$. Concurrently, to mitigate the potential issue of multicollinearity arising from the inclusion of numerous variables, we implement the Variance Inflation Factor (VIF) as a robustness check, serving as a measure to assess the degree of multicollinearity among explanatory variables (Akinwande *et al.* 2015, Thompson *et al.* 2017). Our test results suggest that no multicollinearity issues are present in this context, and the predictive performance remains unaffected by multicollinearity.

3.1.2. Principle component model. In quantifying commodity prices, an alternative approach involves constructing a commodity price index through the application of Principal Component Analysis (PCA) (Abdi and Williams 2010):

$$\begin{aligned} H_P \ : \ \pi_{t+h} &= \phi \pi_t + \psi_x (x_t - \rho_x x_{t-1}) \\ &\quad + \psi_z (z_t - \rho_z z_{t-1}) + \varepsilon_{\pi,t}, \quad h = 3, 6, 9, 12, \end{aligned} \tag{3}$$

In the model definition H_P above, the commodity prices are standardized to ensure a uniform mean and variance, with a mean of 0 and a variance of 1: $K_{ij} = \frac{x_{ij} - \bar{x}_j}{se_j}$, where K_{ij} is standardized data. Subsequently, the covariance matrix C of the standardized data matrix K_{ij} is computed: $C = \frac{1}{n-1} K^\top K$, where the covariance matrix C delineates the linear relationships among the various commodities. Deriving the eigenvalues λ_j and corresponding eigenvectors v_j of the covariance matrix C: $C\mathbf{v}_j = \lambda_j \mathbf{v}_j$. By arranging the eigenvalues in descending order, we select the eigenvector v_1 corresponding to the largest eigenvalue λ_1 as the first principal component: $PC1 = Kv_1$. Among them, $PC1$ serves as our target variable for conducting regression-based forecasts as a commodity price index. The predictive performance of H_P is slightly inferior to that of H_S. Despite some of the limitations of the PCA†, it still demonstrates a considerable forecasting capability for inflation, as reflected in the forecast results.

3.1.3. Single commodity models. To evaluate the predictive power of a single commodity on inflation, we employ it as a regressor across twelve separate regression analyses:

$$\begin{aligned} H_i \ : \ \pi_{t+h} &= \phi \pi_t + \psi_x (x_t - \rho_x x_{t-1}) + \psi_z (z_t - \rho_z z_{t-1}) \\ &\quad + \varepsilon_{\pi,t}, \quad h = 3, 6, 9, 12, \ i = 1, \ldots, 12. \end{aligned} \tag{4}$$

Although our primary focus is not on the predictive power of a single commodity on inflation, we included this aspect as a robustness check. Based on the results of empirical testing, the predictive outcomes closely align with those of H_S and H_P, indicating that individual commodities possess a similarly robust predictive capacity for inflation.

3.1.4. Benchmark models. To provide a more comprehensive exposition of the performance of our inferred model, we have referenced and evaluated models from Tule *et al.* (2019) as our benchmark models.‡ Notably they did not include futures prices in their modeling. More specifically, we use the component models and single commodity models from their paper as benchmarks for our corresponding component and single commodity models, respectively, to ensure fair comparisons. We list benchmark models for the component models and single commodity models as follows with a subscript 0 for each benchmark, for $h = 3, 6, 9, 12$,

$$\begin{aligned} H_{0,S} \ : \ \pi_{t+h} &= \alpha + \sum_{i=1}^{12} \beta_i x_{i,t} + \delta z_t + \sum_{i=1}^{12} \psi_{i,x} (x_{i,t} - \rho_{i,x} x_{i,t-1}) \\ &\quad + \psi_z (z_t - \rho_z z_{t-1}) + \varepsilon_{\pi,t}, \end{aligned} \tag{5}$$

$$\begin{aligned} H_{0,P} \ : \ \pi_{t+h} &= \alpha + \beta x_t + \delta z_t + \psi_x (x_t - \rho_x x_{t-1}) \\ &\quad + \psi_z (z_t - \rho_z z_{t-1}) + \varepsilon_{\pi,t}, \end{aligned} \tag{6}$$

$$\begin{aligned} H_{0,i} \ : \ \pi_{t+h} &= \alpha + \beta x_{i,t} + \delta z_t + \psi_{i,x} (x_{i,t} - \rho_{i,x} x_{i,t-1}) \\ &\quad + \psi_z (z_t - \rho_z z_{t-1}) + \varepsilon_{\pi,t}, \quad i = 1, \ldots, 12. \end{aligned} \tag{7}$$

3.2. Forecasting procedure

Building upon the established model, we partition the full sample into in-sample period (1996:M01 − 2019:M06) and out-of-sample period (2019:M07 − 2023:M07), following the approach of Bossaerts and Hillion (1999) and Ang and Bekaert (2007) Throughout the model fitting process, we define, for $h = 3, 6, 9, 12$,

$$\Theta_h := (\phi, \psi_{i,x}, \psi_{i,z}, \rho), \quad \rho := (\rho_{i,x}, \rho_{i,z}), \tag{8}$$

† There are several limitations associated with the use of PCA in this context. By reducing the dimensionality of the data, it may result in the loss of information specific to individual commodities. PCA relies on the assumption that the principal components with the largest variance are also the most informative in terms of forecasting. However, in some cases, components with smaller variances might still hold important predictive information for inflation but are not retained in the final model.

‡ Tule *et al.* (2019) incorporated the structural break of a single commodity into the model: $\sum_{r=1}^{k} \phi_r D_{r,t}$. Structural breaks were represented using dummy variables, where $D_t = 1$ if $t \geq BreakDate$ and zero otherwise. Given that a single commodity may exhibit multiple structural breakpoints, the summation operator is employed to account for these occurrences (Bai and Perron 2003, Tule *et al.* 2019). Our findings indicate that accounting for structural breaks does not significantly enhance the predictive accuracy of the model.

$$\hat{\pi}_{t+h}\left(\hat{\Theta}_h\right) := \hat{\phi}\pi_t + \hat{\psi}_{i,x}(x_{i,t} - \rho_{i,x}x_{i,t-1}) + \hat{\psi}_{i,z}(z_{i,t} - \rho_{i,z}z_{i,t-1}), \tag{9}$$

where $\widehat{\Theta}_h = (\widehat{\rho}, \widehat{\psi}_{i,x}, \widehat{\psi}_{i,z}), \widehat{\rho} := (\widehat{\rho}_{i,x}, \widehat{\rho}_{i,z})$ denotes the ordinary least squares (OLS) estimated parameters, through which we derive the estimated values of $\widehat{\pi}_{t+h}$, representing the inflation forecasts required within our model. The parameter estimates $\widehat{\Theta}_h$ obtained from the in-sample analysis are applied to forecast the values of $\widehat{\pi}_{t+h}(\widehat{\Theta}_h)$ for in- and out-of-sample segments.

To evaluate predictive performance, Root Mean Squared Error (RMSE) is employed.† Moreover, we incorporate the corrected goodness of fit $R^2_{\text{Adj.}}$, also known as the adjusted R^2. The formula for this is as follows: for $h = 3, 6, 9, 12$,

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum\left(\pi_{t+h} - \hat{\pi}_{t+h}\right)^2},$$

$$R^2_{\text{Adj.}} = 1 - \left(\frac{(1-R^2)(n-1)}{n-k-1}\right),$$

$$\text{where } R^2 = 1 - \frac{\sum_t(\hat{\pi}_{t+h} - \pi_{t+h})^2}{\sum_t(\bar{\pi}_{t+h} - \pi_{t+h})^2}, \tag{10}$$

and n is the sample size in the regression, k represents the number of independent variables, π_{t+h} represents the $(t+h)$th observed value and $\widehat{\pi}_{t+h}$ represent the $(t+h)$th predicted value. $\overline{\pi}_{t+h}$ denotes the mean value. Our assessment of the performance of the model primarily relies on the aforementioned indicators.

4. Data and preliminary analyses

The monthly data spans a period of 27 years, from June 1996 to July 2023. The in-sample period spans from June 1996 to July 2019, while the out-of-sample period extends from July 2019 to June 2023, thereby designating a four-year horizon for the out-of-sample data. Regarding food commodities, we consult literature that frequently mentions certain food items, which also constitute categories of food that hold a high share in the Consumer Price Index (CPI) expenditure. Similarly, these items represent some of the more active food commodities within the American market. We primarily utilize futures prices, incorporating spot prices as a robustness check. All futures and spot prices utilized in our analysis were sourced from Bloomberg. Specifically, livestock commodities (Live Cattle, Lean Hogs, Milk) data were sourced from the Chicago Mercantile Exchange (CME); grain commodities (Corn, Soybean, Wheat, Oat, Rice) were sourced from the Chicago Board of Trade (CBOT, part of the CME Group); and soft commodities (Sugar, Coffee, Cocoa, and Orange Juice) were obtained from the Intercontinental Exchange (ICE). Monthly data points represent the closing (last) prices recorded on the last available trading day of each month. Given that each futures contract has multiple expiration dates, the monthly prices we compile correspond to the contracts maturing closest to that month. For example, the June 1996 price for corn is derived from the June 1996 contract prices. It is important to note that not all commodities have contracts maturing every month. For instance, wheat lacks a June expiration contract, so we instead use price data from the July contract for the month of June. We select the civilian unemployment rate (UNEM) as the economic activity index. To measure inflation, we extract two components from the Consumer Price Index for All Urban Consumers (CPI-U) from the Federal Reserve Economic Data (FRED) database: headline inflation and food inflation. Headline inflation is derived from the index for all items in the U.S. City Average, while food inflation is based on the index for food in the U.S. City Average. Indicators of economic activity related to the United States are also obtained from the FRED database. A detailed description of all variables is presented in table 1.

Regarding the mean, food inflation is marginally higher than headline inflation, with the former's standard deviation being slightly lower than the latter's. Regarding kurtosis and skewness, the distribution of food inflation exhibits a relatively positive skewness, suggesting a distribution with thinner tails. Conversely, headline inflation displays a negative skewness which is leptokurtic, indicative of a distribution with fatter tails. This may imply the presence of outliers within the data. All other food commodity futures are characterized by thin tails, with the exception of Juice.

Notably, the skewness and kurtosis of futures prices are lower than those of spot prices, indicating that futures prices are relatively more stable and experience fewer extreme price fluctuations. Nevertheless, our findings suggest that both possess comparable predictive power.

Table 2 exhibits the correlation coefficients among twelve commodities. These metrics gauge the degree of linear correlation between two variables, with their values ranging from -1 to $+1$. A value closer to 1 denotes a strong positive correlation. The results indicate the absence of negative values, signifying no evidence of negative correlations among these commodity prices. Both futures prices and spot prices exhibit a certain degree of linear relationship.

Subsequently, we performed the Augmented Dickey-Fuller (ADF) test on the differenced components of the constructed model $(x_{i,t} - \rho_{i,x}x_{i,t-1})$ and other regressors. As shown in table 3, we ensured that all regression variables are stationary.‡

We also conduct tests for normality, autocorrelation and heteroskedasticity of the regression residuals of the H_S and H_P models with futures prices, and the results are presented in Appendix A.3. The results suggest positive autocorrelation in the long-term case and heteroskedasticity. However,

† We also conducted tests for Mean Squared Error (MSE) and Mean Absolute Error (MAE), and their outcomes were consistent with those of RMSE. To streamline the presentation of the results, we have omitted the MSE and MAE values from the final table. RMSE is usually employed in quantifying the divergence between model predictions and actual observations. Owing to its dimensional parity with the observations, it facilitates a more intuitive interpretation.

‡ The stationarity test on prices levels is shown in Appendix (table A2).

Table 1. Descriptive statistics for various commodities and inflation rates. *Currency* : *U.S.dollar*.

	Max		Min		Mean		Median		Std. Dev.		Skewness		Kurtosis	
	Futures	Spot	Futures	Spot	Futures	Spot	Futures	Spot	Futures	Spot	Futures	Spot	Futures	Spot
Food Inflation	0.0138		−0.0038		0.0023		0.0019		0.0025		1.1245		2.17	
Headline Inflation	0.0137		−0.0179		0.0021		0.002		0.0029		−0.9346		8.2091	
UNEM	14.7		3.4		5.74		5.4		1.79		1.38		1.94	
Live Cattle	1.68	1.82	0.59	0.57	1.01	1.01	0.97	0.97	0.28	0.28	0.42	0.49	−0.83	−0.58
Lean Hogs	1.27	1.33	0.31	0.29	0.71	0.70	0.67	0.67	0.16	0.17	0.44	0.68	0.35	0.63
Corn	6.96	8.18	1.92	1.80	3.85	3.91	3.58	3.58	1.21	1.64	0.46	0.85	−0.73	−0.28
Soybean	17.57	17.65	4.21	4.21	9.34	9.31	8.92	8.94	2.89	3.46	0.28	0.40	−0.69	−0.87
Sugar	0.26	0.34	0.05	0.05	0.14	0.14	0.12	0.12	0.05	0.06	0.27	0.84	−0.64	−1.00
Coffee	2.98	2.99	0.47	0.43	1.30	1.37	1.21	1.30	0.46	0.50	0.66	0.80	0.73	0.66
Cocoa	3521	3757	745	704	2106	2135	2170	2217	669.92	698.73	−0.06	−0.08	−0.94	−0.97
Juice	3.16	2.82	0.58	0.56	1.26	1.23	1.26	1.23	0.38	0.41	1.02	0.96	0.44	1.03
Rice	21.78	21.48	3.55	3.51	11.33	11.08	11.35	11.08	3.62	3.80	0.03	−0.02	−0.65	−0.56
Milk	21.7	25.20	9.65	8.57	15.35	15.51	15.51	15.29	2.51	3.57	0.35	0.45	−0.73	−0.35
Oat	5.74	7.30	0.97	0.97	2.58	2.57	2.61	2.36	1.06	1.19	0.46	1.42	3.15	0.46
Wheat	10.46	10.88	2.43	2.33	5.27	5.00	5.26	4.78	1.81	1.88	0.40	0.66	−0.70	−0.19

Table 2. Correlation matrix for futures and spot price.

	Live Cattle	Lean Hogs	Corn	Soybean	Sugar	Coffee	Cocoa	Juice	Rice	Milk	Oat	Wheat
Futures Price												
Live Cattle	1	0.72	0.79	0.73	0.57	0.49	0.71	0.67	0.74	0.74	0.74	0.76
Lean Hogs	0.72	1	0.78	0.77	0.48	0.56	0.65	0.53	0.78	0.67	0.75	0.76
Corn	0.79	0.78	1	0.78	0.73	0.61	0.77	0.71	0.91	0.73	0.91	0.90
Soybean	0.73	0.77	0.78	1	0.69	0.61	0.78	0.75	0.93	0.76	0.78	0.95
Sugar	0.57	0.48	0.73	0.69	1	0.31	0.69	0.50	0.66	0.41	0.59	0.77
Coffee	0.49	0.56	0.61	0.61	0.31	1	0.64	0.50	0.67	0.54	0.50	0.77
Cocoa	0.71	0.65	0.77	0.78	0.69	0.64	1	0.59	0.76	0.59	0.60	0.76
Juice	0.67	0.53	0.71	0.75	0.50	0.50	0.59	1	0.58	0.54	0.56	0.58
Rice	0.74	0.78	0.91	0.93	0.66	0.67	0.76	0.58	1	0.75	0.71	0.92
Milk	0.74	0.67	0.73	0.76	0.41	0.54	0.59	0.54	0.75	1	0.71	0.73
Oat	0.74	0.75	0.91	0.78	0.59	0.50	0.60	0.56	0.71	0.71	1	0.92
Wheat	0.76	0.76	0.90	0.95	0.77	0.77	0.76	0.58	0.92	0.73	0.92	1
Spot Price												
Live Cattle	1	0.64	0.63	0.72	0.57	0.49	0.71	0.62	0.62	0.63	0.66	0.61
Lean Hogs	0.64	1	0.64	0.70	0.54	0.57	0.69	0.50	0.56	0.56	0.63	0.56
Corn	0.63	0.64	1	0.93	0.73	0.70	0.72	0.66	0.82	0.61	0.82	0.90
Soybean	0.72	0.70	0.93	1	0.69	0.64	0.69	0.60	0.87	0.67	0.70	0.85
Sugar	0.57	0.54	0.73	0.69	1	0.74	0.69	0.66	0.67	0.41	0.59	0.69
Coffee	0.49	0.57	0.70	0.64	0.74	1	0.64	0.50	0.56	0.57	0.50	0.65
Cocoa	0.71	0.69	0.72	0.69	0.69	0.64	1	0.50	0.70	0.50	0.60	0.65
Juice	0.62	0.50	0.66	0.60	0.66	0.50	0.50	1	0.51	0.50	0.51	0.65
Rice	0.62	0.56	0.82	0.87	0.67	0.56	0.70	0.51	1	0.65	0.67	0.84
Milk	0.63	0.56	0.61	0.67	0.41	0.57	0.50	0.50	0.65	1	0.66	0.67
Oat	0.66	0.63	0.82	0.70	0.59	0.50	0.60	0.51	0.67	0.66	1	0.85
Wheat	0.61	0.56	0.90	0.85	0.69	0.65	0.65	0.65	0.84	0.67	0.85	1

as noted in Wooldridge (2016, Section 12.6), the presence of heteroskedasticity has no bearing on the unbiasedness or consistency of the OLS estimators. Similarly, according to Wooldridge (2016, Theorems 10.1 and 11.1), it is clear that autocorrelation also does not affect the unbiasedness or consistency of these estimators. Moreover, since the primary goal of our study is forecasting rather than inference, we are more concerned with the model's actual predictive errors (RMSE) rather than the statistical significance of coefficients. In this context, deviations from strict normality, autocorrelation or heteroskedasticity in the residuals do not materially affect the accuracy of 'point' forecasts.

5. Discussion of results

5.1. *Forecasting food inflation using futures price: H_S and H_P models*

Based on the methodology mentioned previously, the predictive model was constructed based on varying sets of price information. Our research initially constructs forecast combinations and index methods grounded in these price attributes. Table 4 presents the model's forecast in-sample and out-of-sample results for food inflation evaluated across four forecasting horizons: $h = 3$, $h = 6$, $h = 9$, and $h = 12$. The

Table 3. ADF test.

	Futures Price		Spot Price	
	Test Statistic	p-value	Test Statistic	p-value
Live Cattle	− 11.24	0.00	− 3.66	0.00
Lean Hogs	− 12.08	0.00	− 5.83	0.00
Corn	− 16.88	0.00	− 6.13	0.00
Soybean	− 4.47	0.00	− 4.04	0.00
Sugar	− 10.89	0.00	− 5.29	0.00
Coffee	− 19.47	0.00	− 6.15	0.00
Cocoa	− 21.64	0.00	− 5.81	0.00
Juice	− 6.93	0.00	− 6.91	0.00
Rice	− 17.86	0.00	− 5.06	0.00
Milk	− 8.38	0.00	− 5.96	0.00
Oat	− 15.63	0.00	− 5.05	0.00
Wheat	− 7.08	0.00	− 6.27	0.00
UNEM	− 4.61	0.00	− 4.61	0.00
Lag Inflation	− 4.11	0.00	− 4.11	0.00

Note: The optimal value of lag is selected by minimizing the Akaike information criterion (AIC).

assessment primarily employs metrics such as RMSE and adjusted R^2 to gauge the model's predictive accuracy and explanatory power. Examining the RMSE results, we observe a slight increase in forecast error for food inflation as the forecasting horizon extends, indicating a gradual rise in prediction error over time. The adjusted R^2 metric demonstrates robust explanatory power for shorter horizons, with the model accounting for over 50%. However, as the forecast period lengthens, the values decrease, reflecting a marginal reduction in explanatory strength for long-term predictions. The H_S model demonstrates marginally superior in-sample performance compared to H_P. In constructing the H_P price index, however, certain food commodity price trends were inadvertently attenuated, resulting in predictive outcomes that were less optimal than those achieved through the component model. Nevertheless, the models we developed after addressing non-stationarity consistently outperformed the baseline model. The predictive accuracy and explanatory power for food inflation are markedly superior to those for headline inflation, suggesting that the volatility in food inflation may be more readily captured by the existing model. In contrast, headline inflation forecasts appear to be influenced by a broader set of complex factors, resulting in comparatively lower model performance. These findings underscore the model's robust predictive capabilities. The results for headline inflation forecasting with futures prices are provided in table A.5.1 of the Appendix.†

We further assess the out-of-sample forecasting performance of various regressors relative to the baseline model with futures prices added to the model. Among them, it is interesting to note that the H_P model has a higher out-of-sample adjusted R^2 and superior model performance, which may be attributed to the fact that the PCA method extracts the most dominant data components by descending magnitude after the in-sample model fitting and removes the redundant information by out-of-sample analyses based on the obtained parameters, which makes the model more explanatory and capable of capturing a more accurate inflationary trend. Furthermore, both the H_S and H_P models outperform the benchmark, with lower RMSE values at shorter forecasting windows (e.g. $h = 3$ and $h = 6$), suggesting a distinct advantage in short-term forecasting. Similarly, the model appears well-suited for extended forecasting horizons, such as $h = 9$ and $h = 12$, as indicated by RMSE evaluations.

However, we observe that for food inflation, the adjusted R^2 for the H_S model is generally lower in the out-of-sample results compared to the in-sample results, whereas the H_P model exhibits higher adjusted R^2 in the out-of-sample results. For headline inflation, the adjusted R^2 for both H_S and H_P models are generally higher in the out-of-sample results compared to the in-sample results. The discrepancy in adjusted R^2 between in-sample and out-of-sample results for the H_S model in the case of food inflation may reflect a degree of overfitting, especially given the large number of explanatory variables in that model. In contrast, the H_P model appears to generalize better and capture broader market signals using dimension reduction.

Figure 1 illustrates the forecasted trend lines for H_S and H_P, respectively. It is evident that both models effectively capture inflation trends, performing substantially better than the baseline model ($H_{0,S}$ and $H_{0,P}$). For $h = 3$, no out-of-sample predictions were available for the initial three periods, thus forecasting begins from the fourth period onward. Forecasted trend patterns for other horizons closely resemble those observed at $h = 3$. Forecasted trend lines are shown in the figure A.5.1.

5.2. *Forecasting food inflation using futures price: H_i model*

Table A.5.2 shows in-sample results for single commodity forecasting H_i with benchmark results $H_{0,i}$. Overall, the single commodity approach does not perform as robustly as the previously established models. However, it does provide a measure of insight into the predictability of individual commodity prices. The results indicate that our model outperforms the baseline. Certain commodities, such as juice, exhibit notably strong predictability.

Table A.5.3 shows H_i and $H_{0,i}$ out-of-sample results with futures price, respectively. These results also reveal substantial heterogeneity in the predictive power across different commodities, which is consistent with economic intuitions. For example, futures prices for corn and rice, which are more directly linked to broader economic conditions through food production and global trade, may exhibit relatively stronger inflation forecasting performance. In contrast, commodities such as coffee or sugar may have weaker predictive power due to lower relevance to aggregate price dynamics or more stable pricing patterns. In addition, the predictive power of some commodities, such as wheat, may vary seasonally, while others, like corn, may be sensitive to trade policy, global demand,

† To ensure clarity and focus, we only present the results for food inflation forecasting using futures prices in the main text. All other results, including those for single commodities, headline inflation forecasting, and spot prices, are consolidated and presented in Appendix A.5.

Table 4. Food inflation results with futures price (Full sample).

	h=3		h=6		h=9		h=12	
	RMSE	Adj.R^2	RMSE	Adj.R^2	RMSE	Adj.R^2	RMSE	Adj.R^2
In-sample								
H_S	0.187	0.507	0.202	0.412	0.210	0.363	0.236	0.281
$H_{0,S}$	0.353	0.427	0.371	0.362	0.400	0.333	0.409	0.187
H_P	0.193	0.476	0.206	0.383	0.216	0.328	0.241	0.252
$H_{0,P}$	0.397	0.221	0.408	0.197	0.422	0.184	0.427	0.161
Out-of-sample								
H_S	0.223	0.455	0.230	0.421	0.235	0.395	0.222	0.384
$H_{0,S}$	0.372	0.391	0.380	0.351	0.413	0.312	0.404	0.177
H_P	0.209	0.655	0.215	0.645	0.221	0.637	0.211	0.638
$H_{0,P}$	0.397	0.221	0.408	0.197	0.422	0.182	0.430	0.163

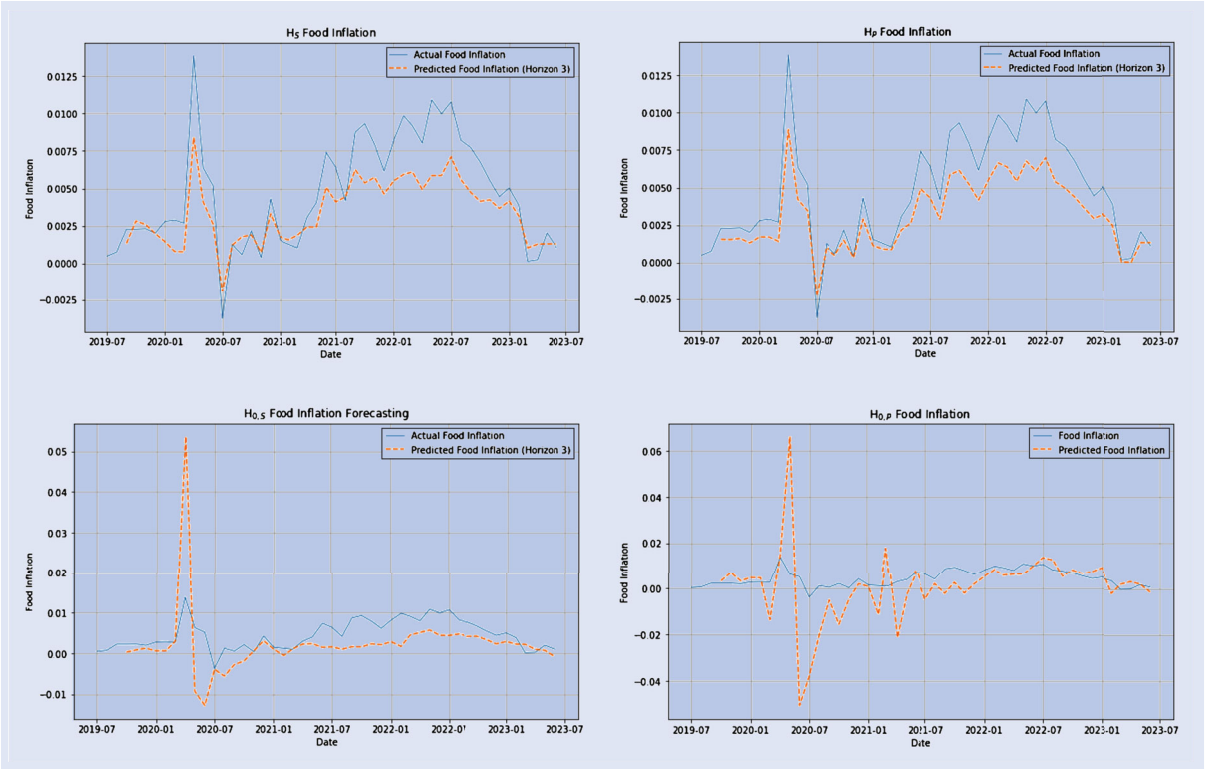

Figure 1. Food inflation forecasting with futures price, $h = 3$.

or geopolitical shocks. These findings highlight the capabilities and limitations of relying on single commodity models and suggest the value of more flexible modeling approaches that can aggregate and adapt to such heterogeneous differences.†

Regardless of the approach used to construct the variables, our model consistently outperforms the baseline model. As observed in the table, for most commodity futures forecasts of inflation, predictions at $h = 12$ exhibit higher adjusted R^2 values and lower RMSE, suggesting that the model performs better over longer forecasting horizons. At present, there is insufficient evidence to explain this phenomenon. However, we hypothesize that longer forecasting periods may, to some extent, smooth out noise within the data. With extended forecasting horizons, the model is more likely to capture long-term trends than short-term fluctuations. For variables like food prices, which might have frequent fluctuations, short-term forecasts may contain significant noise, whereas long-term forecasts better reflect persistent trends with reduced noise impact.

Figure A.5.2 illustrates the three-period-ahead inflation forecasts based on the prices of 12 commodity futures, each of which demonstrates some level of predictability. However, the influence of individual commodities on inflation remains limited.‡ These single commodity models' results can also serve as benchmarks and help evaluate and highlight the performance of both the single component and principal component models, designed to integrate market information from multiple commodities in a more flexible way. Of

† We thank an anonymous referee for pointing out these findings.

‡ In our efforts to forecast headline inflation, we observed that the influence of individual commodities on headline inflation was too minimal to meaningfully reflect their predictive role within the model. The results were somewhat unsatisfactory. Therefore, we have chosen not to present the headline inflation forecast outcomes.

course, one can also try to construct improved indices by exploring more adaptive and flexible (or even nonlinear) weighting schemes via cointegration techniques or machine learning-based methods.

5.3. Robustness checks

5.3.1. Spot price forecasting. To further demonstrate the model's predictive power, we employ spot price forecasts as a robustness check. Spot prices directly mirror the current supply and demand dynamics in the market, serving as an immediate indicator of inflation. If the inflation rate projected by futures prices aligns with that indicated by spot prices, it demonstrates that futures prices can effectively forecast inflation. By conducting a robustness check via spot prices, the model could more comprehensively validate the accuracy of its forecasts, mitigating biases associated with reliance on a single data source. The results are presented in tables A.5.4 and A.5.5. Tables A.5.6 and A.5.7 further confirm the model's robustness. The results align closely with those obtained from forecasting inflation using futures prices. Regardless of the approach applied, the model's predictive capacity is compellingly demonstrated. Figures A.5.3 and A.5.4 illustrate the forecasted trend lines for H_S and H_P, respectively. It is evident that both models effectively capture food inflation trends, performing substantially better than the baseline model ($H_{0,S}$ and $H_{0,P}$). Figure A.5.5 illustrates the three-period-ahead inflation forecasts derived from the spot prices of each of the 12 food commodities.

5.3.2. Subsample analysis. For further examination of our model's robustness over significant events, we perform a subsample analysis for the post-crisis/pre-COVID period (2009–2020), thereby allowing a clearer separation of the effects of the 2008 financial crisis and the COVID-19 pandemic. More specifically, we split our dataset as follows:

- The subsample is from July 2009 to February 2020 (2009M7 − 2020M2): in-sample period is from July 2009 to January 2018 (2009M7 − 2018M1), out-of-sample period is from February 2018 to February 2020 (2018M2 − 2020M2).

We have applied the H_S and H_P models as examples of forecasting food inflation using futures prices. Table A.5.8 shows the results for the subsample.

It can be observed that the results obtained from the subsample analysis echo the main finding from the full sample in table 4 (hereafter full-sample findings). Across the subsample period, the in-sample results for H_S and H_P display consistent patterns with the full-sample findings. Specifically, H_S tends to have a slightly lower RMSE and higher adjusted R^2 values, indicating better in-sample fitting and accuracy.

Moreover, if we exclude the 2008 crisis and COVID-19 (2009M7-2020M2), the two models show similar out-of-sample RMSEs across all forecasting horizons. However, H_P has higher adjusted R^2 values, indicating better explanatory performance out-of-sample. Therefore, this suggests that during relatively stable economic periods, the principal component model may better capture variations in inflation while maintaining comparable forecast accuracy to H_s, which has more explanatory variables.

The subsample results in Tables 6.1 broadly echo the full-sample findings: H_S shows better in-sample fit, while H_P demonstrates stronger out-of-sample generalization, especially during volatile periods such as the COVID-19 era. This reflects a trade-off between model flexibility and robustness.

6. Conclusion

Our study explores the potential of commodity futures prices for forecasting inflation, with a focus on both short- and long-term forecasts (3-month, 6-month, 9-month, and 12-month horizons). Different methodologies for constructing futures price indices are employed to assess various predictive outcomes. Based on forecasting performance metrics such as RMSE and $R^2_{\text{Adj.}}$, it is evident that indices constructed using a simple component approach or PCA index outperform the benchmark model by Tule *et al.* (2019), demonstrating superior out-of-sample fit. While model performance showed a slight decline as the forecast horizon increases, the results for the one-year horizon remained comparable to those of the short-term forecast ($h = 3$), indicating the model's capacity to capture long-term trends effectively. Moreover, we observed that the PCA-based model demonstrates stronger generalization ability out-of-sample. Robustness checks using spot prices and the segmented analyses confirmed the consistency of these findings.

Importantly, the practical implications of our findings are notable for policymakers and economic analysts. Futures-based inflation forecasts can serve as early-warning tools, enabling central banks and economic agencies to adopt more proactive monetary and fiscal strategies. However, reliance on commodity futures also entails limitations. Market-based signals can be distorted by speculative behavior, supply shocks, and geopolitical events. To address these limitations and improve model performance, future research would incorporate global trade flows and climate-related data to better account for international and environmental factors influencing food prices. Methodologically, it might also be promising to explore more flexible forecasting techniques, such as cointegration and machine learning methods (e.g. LASSO, random forests, neural networks).

Disclosure statement

No potential conflict of interest was reported by the author(s).

Supplemental data

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A. Appendix

A.1. First order autocorrelation coefficient

Table A1. First order autocorrelation coefficient ρ, calculated by $\rho = \frac{\sum_{t=2}^{n}(X_t-\bar{X})(X_{t-1}-\bar{X})}{\sum_{t=1}^{n}(X_t-\bar{X})^2}$, where $\bar{X}$ is mean value of variable and X_t denotes the value of the variable at time t.

	$\rho_{\text{Futures Price}}$	$\rho_{\text{Spot Price}}$
Live Cattle	0.976	0.960
Lean Hogs	0.994	0.992
Corn	0.997	0.996
Soybean	0.991	0.990
Sugar	0.988	0.992
Coffee	0.998	0.999
Cocoa	0.986	0.987
Juice	0.922	0.960
Rice	0.996	0.989
Milk	0.997	0.998
Oat	0.995	0.997
Wheat	0.998	0.997
UNEM	0.996	0.996

Note: The value of ρ ranges between -1 and 1, with values approaching 1 indicating a strong positive correlation between the current and previous period observations, thereby suggesting that the variable exhibits a pronounced degree of persistence.

A.2. Stationarity test on prices in levels

We conduct the Augmented Dickey-Fuller (ADF) test on the original price data based on minimizing the Akaike information criterion (AIC). It indicates that the series is non-stationary. Therefore, we apply differencing to the price series to achieve stationarity before proceeding with further analysis.

Table A2. ADF test on price levels based on minimizing the AIC.

	Futures Price		Spot Price	
	Test Statistic	p-value	Test Statistic	p-value
Live Cattle	−0.51	0.89	−0.32	0.92
Lean Hogs	−2.69	0.08	−2.74	0.07
Corn	−1.63	0.47	−1.39	0.59
Soybean	−1.27	0.65	−1.14	0.70
Sugar	−1.75	0.41	−1.46	0.55
Coffee	−2.42	0.17	−2.70	0.07
Cocoa	−1.54	0.52	−1.65	0.46
Juice	−0.32	0.92	−0.88	0.80
Rice	−1.68	0.44	−1.51	0.53
Milk	−4.24	0.00	−5.96	0.00
Oat	−1.37	0.60	−2.20	0.20
Wheat	−1.20	0.67	−2.05	0.27

Table A3. Residual diagnostics and variable tests.

	Normality of residuals Jarque-Bera (p-value)	Autocorrelation Durbin-Watson statistic
h=3		
H_S	0.109	2.252
H_P	0.191	1.934
h=6		
H_S	0.488	2.067
H_P	0.365	1.802
h=9		
H_S	0.589	1.880
H_P	0.373	1.481
h=12		
H_S	0.018	1.632
H_P	0.264	1.325

A.3. Residual test results for normality, autocorrelation and heteroskedasticity

In the following table A3, we provide residual normality and autocorrelation test results with the Jarque-Bera (JB) test and the Durbin-Watson (DW) statistic, respectively. As shown in our results, the test values for short- and mid-term horizons ($h = 3, 6, 9$) are close to 2, implying that residuals for them are approximately normally distributed and exhibit no significant autocorrelation (DW statistic $\approx$ 2). For the long-term horizon ($h = 12$), the residuals are positively serially correlated.

We present the Lagrange Multiplier (LM) test results on time-varying conditional heteroskedasticity of regression residuals for the H_S and H_P models with future price in table A4. The LM statistic is used for testing the presence of time-varying autoregressive conditional heteroskedasticity (ARCH) effect in the residual series. Specifically, it tests the null hypothesis that all ARCH parameters (in the ARCH(q) model, $q = 3, 6, 9, 12$ in our paper) are equal to zero. The LM statistic is obtained from the regression of squared residuals on q lagged squared residuals, i.e. $\text{LM} = T \times R^2$, where T is the number of observations and R^2 is the coefficient of determination for the ARCH(q) LM test regression. Under the null hypothesis of homoskedasticity, the LM statistic should follow a Chi-squared distribution. A large LM value provides sufficient evidence to reject the null hypothesis, indicating the presence of an ARCH effect. The results indicate that we should reject the null hypothesis and conclude there is an ARCH effect up to 12 lags.

A.4. Multicollinearity check

In constructing the H_S model, given the abundance of variables and potential linear correlations among them, we considered employing the Variance Inflation Factor (VIF) to test for multicollinearity. Upon testing, we found that no commodities - whether futures or spot prices - required exclusion from our model due to multicollinearity, as presented in table A5.

Table A4. Conditional Heteroscedasticity test with Lagrange Multiplier (LM) statistic.

	ARCH(3)		ARCH(6)		ARCH(9)		ARCH(12)	
	LM Statistic	*p*-value	LM Statistic	*p*-value	LM Statistic	*p*-value	LM Statistic	*p*-value
Live Cattle	61.39	0.00	62.78	0.00	63.12	0.00	63.50	0.00
Lean Hogs	46.99	0.00	47.53	0.00	48.27	0.00	48.61	0.00
Feeder Cattle	74.75	0.00	76.26	0.00	76.64	0.00	76.84	0.00
Corn	46.75	0.00	47.95	0.00	48.32	0.00	48.52	0.00
Soybean	59.04	0.00	60.55	0.00	60.88	0.00	61.00	0.00
Sugar	85.49	0.00	86.70	0.00	86.81	0.00	86.89	0.00
Coffee	58.68	0.00	59.61	0.00	59.82	0.00	59.91	0.00
Cocoa	87.98	0.00	89.24	0.00	89.31	0.00	89.45	0.00
Juice	76.05	0.00	77.22	0.00	77.28	0.00	77.30	0.00
Rice	61.79	0.00	63.71	0.00	63.91	0.00	64.03	0.00
Milk	51.39	0.00	52.76	0.00	53.47	0.00	53.98	0.00
Oat	47.57	0.00	49.41	0.00	49.52	0.00	49.65	0.00
Wheat	49.51	0.00	51.43	0.00	51.55	0.00	51.65	0.00
UNEM	67.32	0.00	67.63	0.00	67.97	0.00	68.00	0.00

Table A5. VIF test for future and spot prices.

VIF	Futures Price	Spot Price
Live Cattle	1.26	1.60
Lean Hogs	1.13	1.25
Corn	2.29	2.39
Soybean	2.05	2.05
Sugar	1.15	1.15
Coffee	1.17	1.17
Cocoa	1.14	1.15
Juice	1.37	1.22
Rice	1.32	1.34
Milk	1.10	1.11
Oat	1.35	1.34
Wheat	1.73	1.73
UNEM	1.26	1.22