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Can futures markets provide useful real-time forecasts of period average commodity prices? We consider seventeen primary commodities across energy, metals, and agricultural markets and find that futures-based forecasts of period averages outperform the (end-of-period) random walk forecast for the majority of commodities. We document that the prior mixed evidence on the usefulness of futures-based forecasts was driven by the time-sampling of the futures and no-change benchmark data, as well as the forecast evaluation period examined. We show that non-parametric approaches based on the most recent trading data (in lieu of averaging) are the most accurate. Results suggest that academics, policymakers, and industry can consider utilizing futures prices as forecasts of commodity prices.

JEL classification: C1, C53, G13, G15, Q47
Keywords: Forecasting and Prediction Methods, Primary Commodities, Futures Market

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1 Introduction

Primary commodities play an indispensable role in producing a broad array of goods and services, shaping global trade, influencing aggregate price levels, and affecting broader economic outcomes (Gelos and Ustyugova, 2017). These commodities are also central to ongoing global decarbonization efforts. For example, the expected rise in demand for metals, essential for electrification and batteries, highlights their role in transitioning to a lower carbon emission energy system (Bazilian et al., 2023). Similarly, bio-based feedstocks present a potential pathway to decarbonize liquid fuel markets that in the future might increasingly compete with fossil-based alternatives (Tsiropoulos et al., 2015). Economic decisions today are made on expectations of average future commodity price levels and the relative prices of commodities. These average real price levels (rather than point-sampled returns used in finance) are of primary interest, as averages reflect macroeconomic conditions as well the flow of costs and revenues over time. Companies, policymakers, and researchers generate, and are interested in the accuracy of, predictions of average commodity price levels.

One approach to forecasting primary commodity prices is to utilize prices of futures contracts as a forecast of the spot price. This approach has practical benefits, as futures market data is publicly available, continuously updated, and is based on the real-time decisions of market participants. Yet, despite the practical convenience of futures-based forecasts, empirical evidence of the usefulness of futures-based forecasts for the commodity price level has been mixed (for example, Kumar, 1992; Chernenko et al., 2004; Alquist and Kilian, 2010; Chinn and Coibion, 2014; Ellwanger and Snudden, 2023b). Thus, the motivating question for this research is: *Are futures markets useful real-time predictors of the real average spot price of primary commodities?* Theoretically, futures markets can provide an unbiased estimate of futures prices (Fama, 1970; Fama and French, 1987; Hansen and Hodrick, 1980; Bilson, 1980; Beck, 1994), but empirically it is an open question whether futures markets can outperform the random walk no-change forecast.

To reconcile the existent mixed evidence, we provide a review of the methods used in prior studies, detailed in section 2. We identify three suggestions for improvement on methods utilized in prior studies examining price forecasts of *period average* commodity prices.

Firstly, prior analyses of period average forecasts are shown to have averaged futures prices over some period (typically averaging daily values over a month) in the construction of forecasts, which would be expected to reduce forecast accuracy, especially at shorter horizons. This loss in accuracy is intuitive, as a meaningful shock in the later part of the period will not be fully incorporated due to averaging over trading days before the shock (Tiao, 1972; Amemiya and Wu, 1972; Lütkepohl, 1984; Kumar, 1992).

Consider an intuitive recent example. Russia invaded Ukraine on February 24, 2022. The day before the invasion, Brent crude futures for April 2022 were trading at $96.84, and futures markets were in backwardation (i.e. prices were anticipated to fall in coming months). But by the first week of March 2022, Brent crude surpassed $118 per barrel. Simply averaging the entire month of futures markets values within February 2022 would not fully incorporate information about this globally significant geopolitical event.

To overcome this potential information loss due to averaging, we will quantify the use of the latest futures market expectations. Moreover, we propose techniques to reconcile the latest expectations of markets with period average forecasts. It is an open empirical question as to whether using the most recent trading information in lieu of averages meaningfully improves forecast accuracy across commodity markets.[1]

Secondly, we show that prior studies examining futures-based period average forecasts of primary commodities have evaluated forecast gains relative to the naive benchmark given by the period-average no-change. However, such gains are theoretically expected by construction, even when the daily spot price follows a random walk (Weiss, 1984; Marcellino, 1999). Instead, we follow recent advances and maintain the goal of forecasting the period average but compare against the end-of-period no-change forecast (Ellwanger and Snudden, 2023a), which is equivalent to the random walk forecast used in the literature examining point sampled futures-based forecasts (e.g. Kumar, 1992; Chinn and Coibion, 2014; Kwas and Rubaszek, 2021). This allows us to quantify the differences in forecast accuracy of the two naive forecasts for all commodities, and test futures-based forecasts of period averages against the traditional random walk for the first time.

Lastly, prior studies examining real-time forecasts of period average commodity prices in levels are exclusive to crude oil and retail gasoline. We expand this scope to seventeen prominent commodities of the energy, metals, and agriculture markets. This includes novel analysis of ethanol using recently available futures data. Our real-time forecasts of period averages extends upon prior work examining nominal point-sampled forecasts (Reeve and Vigfusson, 2011; Reichsfeld and Roache, 2011; Chinn and Coibion, 2014) and provides an updated assessment of the broad performance of future-based forecasts over the last decade.

[1] Ellwanger and Snudden (2023b) quantifies the effects of temporal aggregation of futures for forecasts of crude oil, but did not consider other commodities or compare against the (end-of-period) random walk forecast.

Our results can be summarized as follows. First, we find that futures-based forecasts, more often than not, outperform the traditional random walk no-change forecast for most primary commodities for horizons of six months and beyond. Preferred approaches utilize the latest expectations from futures markets in lieu of averaging multiple observed days of trading. For example, short-horizon mean-squared forecast errors can be halved for most commodities by using the closing values at the end of month, compared to the existing practices of averaging futures prices. Similarly, simple non-parametric forecasts generally outperform more complicated parametric approaches. Using these proposed techniques, several commodities are found to be predictable at short horizons and most at horizons of six months and beyond.

Second, we compare forecast accuracy across multiple time horizons, spanning from one month to ten years. Results, and prior-mentioned recommendations, are robust across time horizons. Although, at shorter horizons, energy commodities tend to show some of the largest and consistent gains. For example, both ethanol and retail gasoline show upwards of 20 percent gains at the one-month ahead horizon. Performance for non-precious metal commodities was more diverse, especially at shorter horizons, with only copper, lead, and zinc showing some consistency in short horizon accuracy. Beyond the shortest horizons, the largest gains were seen for copper and nickel. Moreover, while we find little evidence of the predictability of real gold prices, the nominal price of gold shows evidence of predictability starting around the one-year ahead, especially in terms of directional accuracy. Finally, agricultural commodities, in particular corn and soybeans, show predictive improvements at most horizons.

Lastly, our findings reveal two ways in how there have been variations in the performance of futures-based forecasts over time. First, there was an increase in the accuracy of futures-based forecasts around 2010 and forecast accuracy has been generally quite stable thereafter for most commodities. Second, during the past two years of our evaluation period have we observed reduced performance for wheat and natural gas, particularly at longer horizons.

The perhaps most important conclusion is that futures-based forecasts can be utilized as a forecast of period average commodity spot prices broadly across many commodities and forecast horizons simply by using the most recent futures market data available. This simple non-parametric approach is also practical as it can be cost-effective and quick to implement in real time. These findings outlined in this study provide guidance on how researchers, policymakers, and companies can most effectively utilize information in the futures markets to construct forecasts.

The remainder of the paper is structured as follows. Section 2 reviews the literature on using futures prices for predicting future spot prices. Section 3 explores the real-time forecast method, and section 4 discusses the data. Section 5 presents our results, and section 6 concludes.

2 Literature Review

Relevant literature is categorized into two broad categories: forecasts of period-average spot prices and forecasts of point-sampled spot prices. We report assumptions pertaining to temporal aggregation, as they are particularly germane to the current analysis. In addition, we summarize the primary commodities examined, the forecast horizons, and whether the analysis considers real or nominal spot prices. Finally, we detail if the forecasts were conducted out-of-sample and whether the forecasts used real-time methods. Real-time out-of-sample forecasts require that both the data and model estimation only use data available at the time of the forecast.

2.1 Period-Average Forecasts

Existing studies that examine forecasts of period-average commodity prices are summarized in Table 1. Most studies in Table 1 examine monthly average forecasts, while all but one analyze forecasts in levels, and all except four examine real forecasts. Earlier studies typically focused on forecast horizons of one-year ahead, but two-years have become the norm in the last decade. Recent studies, such as Chu et al. (2022) and Ellwanger and Snudden (2023b), have examined horizons for up to five years. Out-of-sample and real-time forecasts are common in recent studies. This literature also focuses on crude oil except for Baumeister et al. (2017) who examines retail gasoline, and Bowman and Husain (2006) who examines metal and agricultural commodities from 1993 to 2003. Our study aims to extend this field by analyzing the usefulness of futures-based forecasts for seventeen primary commodities.

Most studies construct futures-based forecasts by taking a simple *average* of contract values for all days within a month. For example, futures trading prices for the twelfth contract are averages for all days of January 2023 and used as the one-year ahead forecast for January 2024. In this analysis, we will investigate using the most recent futures prices available in lieu of an average. Ellwanger and Snudden (2023b) find that any averaging of daily futures data diminishes forecast accuracy of period averages crude oil prices due to information loss from temporal aggregation. The same result was found for point-sampled forecasts by Kumar (1992). This is intuitive, as averaging dilutes the latest expectations from the market with older ones.

Table 1. Summary of Literature Utilizing Futures Prices as Forecast for Period Average Commodity Prices

Author(s)	Commodity	Frequency	Horizons	Futures Sampling	No-Change Benchmark	Real or Nominal	Level or Returns	Out-of-Sample	Real time
Bowman and Housan (2006)	Agricultural, Metals	Quarterly	1 - 8	Quarterly average	Average	Nominal	Level	Yes	No
Pagano and Pisani (2009)	Crude Oil	Monthly	2 - 12	3rd week average	Average	Nominal	Level	Yes	Yes
Baumeister and Kilian (2012)	Crude Oil	Monthly	1 - 12	Monthly average	Average	Real	Level	Yes	Yes
Alquist et al. (2013)	Crude Oil	Monthly	1 - 12	Monthly average	Average	Real	Level	Yes	Yes
Baumeister and Kilian (2014)	Crude Oil	Quarterly	1 - 4	Quarterly average	Average	Real	Level	Yes	Yes
Manescu and van Robays (2014)	Crude Oil	Quarterly	1 - 11	Monthly average	Average	Real	Level	Yes	Yes
Baumeister et al. (2015)	Crude Oil	M, Q	1 - 24	Monthly average	Average	Real	Level	Yes	Yes
Baumeister and Kilian (2015)	Crude Oil	Monthly	1 - 24	Monthly average	Average	Real	Level	Yes	Yes
	Crude Oil	Quarterly	1 - 8	Quarterly average	Average	Real	Level	Yes	Yes
Drachal (2016)	Crude Oil	Monthly	1	Monthly average	Average	Nominal	Level	Yes	Yes
Wang, Liu, and Wu (2017)	Crude Oil	Monthly	1 - 24	Monthly average	Average	Real	Level	Yes	Yes
Baumeister et al. (2017)	Gasoline	Monthly	1 - 24	Monthly average	Average	Real	Level	Yes	Yes
	Gasoline	Quarterly	1 - 8	Quarterly average	Average	Real	Level	Yes	Yes
Funk (2018)	Crude Oil	Monthly	1 - 24	Last 5 days average	Average	Real	Level	Yes	Yes
Conlon et al. (2020)	Crude Oil	Monthly	1	EoM	Average	Real	Return	Yes	No
Chu et al. (2022)	Crude Oil	Monthly	1 - 60	Monthly average	Average	Nominal	Level	Yes	Yes
Ellwanger and Snudden (2023)	Crude Oil	Monthly	1 - 60	EoM, Average	Average	Real	Level	Yes	Yes

Notes: "Commodities" specifies the commodities examined in the respective study. "Frequency" refers to the frequency at which the forecasts were evaluated. "Forecast Horizon" integers correspond to the unit of time specified by the "Frequency". "Futures Sampling" describes how the futures prices were sampled for the predictions. The "Level or returns" column specifies whether the forecast target is the "level" of the spot price or the "return" on the spot price. The "Out-of-Sample" and "Real-time" columns indicate whether the study employs such forecast methods as defined in the text. A detailed list of references is available in Appendix C.

The sampling of the futures prices in the construction of the forecasts could also have driven the mixed evidence regarding the usefulness of futures-based forecasts. Prior studies that averaged over futures prices had concluded that futures were not particularly useful (e.g.. Alquist and Kilian, 2010; Baumeister and Kilian, 2012). In contrast, studies that did not average over the month concluded that futures exhibit some degree of predictive power (Pagano and Pisani, 2009; Funk, 2018; Ellwanger and Snudden, 2023b). These results are consistent with the potential adverse effects on forecast accuracy from the information loss from temporal aggregation (e.g. Tiao, 1972; Amemiya and Wu, 1972; Lütkepohl, 1984). In this paper, we provide an empirical evaluation of how each method influences the accuracy of futures-based forecasts for the three distinct approaches to sampling futures prices: averaging over the entire month, averaging only the last week of the month, and sampling prices at the end-of-month.

In addition to the forecast itself, the naive benchmark against which the forecast was tested is also potentially important. Notably, all studies shown in Table 1 compared the futures-based forecasts against the period average no-change benchmark. However, improvements relative to the average no-change benchmark are theoretically expected even if the underlying commodity price follows a random walk (Working, 1960; Weiss, 1984; Marcellino, 1999; Ellwanger and Snudden, 2023a). For example, in the context of return regressions for crude oil, Conlon et al. (2022) documents that gains in futures-based forecast for period averages vanishes when point sampled data is used. For the first time, we maintain the goal of forecasting the period average, but test against the traditional random walk hypothesis (the end-of-period no-change, see Ellwanger and Snudden, 2023a) used in finance and the point-sampled literature described in the next section.

2.2 Point-Sampled Forecasts

We now turn our attention to studies that have examined futures-based forecasts of point-sampled commodity spot prices, see Table 2. Point-sampled prices are often utilized in financial applications because profits are accrued between the moments of asset purchase and settlement. Moreover, point-sampling is common practice when calculating returns for the explicit purpose of avoiding spurious predictability (see, e.g. Working, 1960; Bork et al., 2022; Conlon et al., 2022).

Table 2. Summary of Studies Forecasting Point-Sampled Commodity Prices using Futures

Author(s)	Commodities	Frequency	Horizons	Futures Sampling	No-Change Benchmark	Real or Nominal	Level or returns	Out-of-Sample	Real time
Fama and French (1987)	Agri., Livestock, Metals, Wood	Monthly	2-10	EoM	EoM	Nominal	Returns	No	No
Kumar (1992)	Crude Oil	Monthly	1-9	EoM, Ave.	EoM	Nominal	Level	Yes	Yes
Abosedra and Baghestani (2004)	Energy	Monthly	1-12	EoM	EoM	Nominal	Returns	No	No
Chernenko et al. (2004)	Energy	Monthly	3-12	15th day of Month	EoM	Nominal	Returns	No	No
Chinn et al. (2005)	Energy	Monthly	3-12	EoM	EoM	Nominal	Level	Yes	No
Alquist and Kilian (2010)	Crude Oil	Monthly	1-12	Last 5 days average	EoM	Nominal	Level	Yes	Yes
Reeve and Vigfusson (2011)	Agricultural, Animal, Energy, Metals	Monthly	3-12	EoM	EoM	Nominal	Returns	Yes	Yes
Reichsfeld and Roache (2011)	Agricultural, Energy, Metals	Weekly	12-104	EoW	EoW	Nominal	Returns	Yes	No
Alquist et al. (2013)	Crude Oil	Monthly	1-12	Last 5 days average	EoM	Nominal	Level	Yes	Yes
Chinn and Coibion (2014)	Agricultural, Energy, Metals	Monthly	3-12	EoM	EoM	Nominal	Returns	Yes	Yes
Jin (2017)	Crude Oil	Weekly	1-24	EoW	EoW	Real	Level	Yes	No
Miao et al. (2017)	Crude Oil	Weekly	1-8	EoW	EoW	Nominal	Level	Yes	Yes
Conlon et al. (2020)	Crude Oil	Monthly	1	EoM	EoM	Real	Return	Yes	No
Kwas and Rubaszek (2021)	Agricultural, Energy, Metals	Monthly	1-12	EoM	EoM	Nominal	Level	Yes	Yes

See notes of Table 1. "EoM" refers to End-of-Month, and "EoW" to End-of-Week. A detailed list of references is available in Appendix C.

Table 2 shows that studies examining point-sampled forecasts cover a wide variety of commodities, including non-oil energy commodities, agricultural products, and metals. In addition, the majority of these studies focus on returns, with all except two examining nominal forecasts. The majority employ real-time methods. Since Chinn et al. (2005), out-of-sample forecasts have become common practice in these studies.

Such studies also consistently compare forecasts against the point-sampled no-change benchmark, thus testing the traditional random walk null hypothesis. Moreover, most of these studies utilize point-sampled futures to construct forecasts. The exception is Alquist and Kilian (2010) and Alquist et al. (2013), which use an average of the last 5 business days of the month. However, Kumar (1992) examines both end-of-period and alternative forms of averaging for crude oil and finds that any averaging reduces accuracy of out-of-sample point forecasts.

Interestingly, the point forecast literature has been more likely to find that futures prices outperform no-change forecasts. The predictive ability is found to differ across different commodities and forecasting horizons. For example, Chinn et al. (2005), Reeve and Vigfusson (2011), and Chinn and Coibion (2014) show that futures markets are predictive for energy and agricultural commodities over all horizons. In addition, these studies observe limited predictive power of futures prices for precious and base metals. Similar results are found by Reichsfeld and Roache (2011) and Abosedra and Baghestani (2004), who further note that the performance of futures prices depends on market conditions, and the performance is time-varying.

3 Methods

Consistent with the existing literature and standard reporting, the monthly average is the simple average of daily closing prices observed over the calendar month; $\bar{S}_t = \frac{1}{n}\sum_{i=1}^{n} S_{t,i}$. Where $S_{t,i}$ denotes the daily closing spot price on day i of month t, and n is the last day of month t. The nominal monthly average is deflated by the consumer price index to derive the monthly average real price, $\bar{R}_t = \bar{S}_t/p_t$. We utilize all information available in real-time at the end of the month to construct h-month ahead forecasts of the future level of the monthly average real spot price, $E_{t,n}(\bar{R}_{t+h})$.

3.1 Expectations from Futures

How can a forecaster use the information available in the futures market at the end of the month to construct forecasts of the future monthly average spot price? To elucidate, consider a case in which there is no risk premium and settlement and delivery occur on the same day. In this case, the price of a futures contract, $F_{t,i}^{h,d}$, reflects the market's expectations of:

$$F_{t,i}^{h,d} = E_{t,i}(S_{t+h,d}), \tag{1}$$

where d is the day of delivery, h months ahead. This futures price is observed at closing on the i-th day of month t. $E_{t,i}$ stands for the expectation operator, indicating the futures market's expected value based on the information available at closing on day i in month t . Thus, the futures price represents the expected market price for the delivery date in day d in month t.

Consider now the three approaches used to sample futures prices for predicting the level of the period average spot prices.

The first approach is used in Alquist and Kilian (2010) and Funk (2018), where the focus lies on averaging futures prices over the final 3-5 trading days of the month. The former applies this approach to predict the end-of-month spot prices, and the latter employs it to forecast the monthly average real spot prices. The effect of end-of-month averaging is as follows:

$$\tilde{F}_t^{h,d} = \frac{1}{3}\sum_{j=1}^{3} F_{t,n+1-j}^{h,d} = \frac{1}{3}\sum_{j=1}^{3} E_{t,n+1-j}(S_{t+h,d}). \tag{2}$$

This implies that when averaging futures prices, we are averaging over old expectations of the same delivery date in the future. It is not the futures market current expectation of some future average.

The second approach, which is prevalent in existing forecasting applications of monthly average prices (see, e.g., Baumeister and Kilian, 2012; Alquist et al., 2013), uses of the monthly average of the futures price:

$$\bar{F}_t^{h,d} = \frac{1}{n}\sum_{j=0}^{n} F_{t,n-j}^{h,d} = \frac{1}{n}\sum_{j=1}^{d} E_{t+1-j}(S_{t+h,d}) + \frac{1}{n}\sum_{j=d+1}^{n} E_{t+1-j}(S_{t+h-1,d}). \tag{3}$$

Consequently, the monthly average futures price is predicated on prices for two neighboring contracts. Essentially, this approach averages over expectations of the same day in two adjacent months in the future. For example, if d is the middle of the month, the average of $E_{t,n}(S_{t+h,d})$ and $E_{t,n}(S_{t+h-1,d})$ may be an appropriate forecast for the first day of month $t+h$.

The third approach, uses only the latest expectations of the futures market, the closing price on the last trading day of the month, $F_{t,n}^{h,d} = E_{t,n}(S_{t+h,d})$. This approach is intuitively appealing, as the end-of-month futures price reflects the most current expectation of the futures market of the future spot prices. Of course, it is ultimately an empirical question whether this approach can result in more accurate forecasts. In the study, we conduct an empirical evaluation of the three approaches across seventeen primary commodities.

In addition, recall that the objective of this analysis is to forecast the monthly average price of the commodity, $E_{t,n}(\bar{S}_{t+h})$. In contrast, the futures contract may refer to an alternative average period or day d, $E_{t,n}(S_{t+h,d})$. If this is the case, there may be forecast gains from reconciling the markets forecast with the monthly average forecast.[2] That is, the futures market may not directly provide an expectation of the monthly average forecast. For this reason, we carefully review the differences' in the delivery and settlement dates for the different commodities. We also quantify alternative approaches to reconcile any potential differences in markets expectations with the forecasters objective. Both parametric and non-parametric approaches to align the expectations of the point forecast and the monthly average forecast are examined.

3.2 Futures-Based Forecasts

A common way to construct a futures-based forecast of a real spot price is to deflate the futures curve, as follows:

$$\hat{R}_{t+h,d|t} = F_{t,n}^{h,d} / E_{t,n}(p_{t+h|t}), \ \forall\ h \tag{4}$$

where $E_{t,n}(p_{t+h|t})$ is the expected U.S. consumer price deflator h periods ahead. This common practice has been to rewrite this equation using log-percentage spreads of the futures price with maturity h, $F_{t,n}^{h,d}$, over the spot price, $S_{t,n}$, (e.g. Alquist and Kilian, 2010).

$$\hat{R}_{t+h,d|t} = R_{t,n}\left(1 + \ln F_{t,n}^{h,d} - \ln S_{t,n} - E_{t,n}\left(\pi_t^h\right)\right), \ \forall\ h \tag{5}$$

where $E_{t,n}\left(\pi_t^h\right)$ is the expected U.S. inflation rate over the next h periods. This is still a h-months ahead forecast for the delivery period d.

The proposed non-parametric method of Ellwanger and Snudden (2023b) assumes proportionality and uses the futures-market forecast of the spot price on the delivery period $\hat{R}_{t+h,d|t}$ as the forecast of the monthly average $\hat{\bar{R}}_{t+h|t}$. This is particularly appealing for commodities where the delivery period is any day within the month, for example for natural gas, crude oil, and precious metals, see section 4.1. Alternatively, the delivery date may refer to a specific day within a month,

[2] Likewise, if the forecast target is the end-of-month price, $E_{t,n}(S_{t+h,n})$, it may be that $E_{t,n}(S_{t+h,n}) \neq E_{t,n}(S_{t+h,d})$.

for example for base metals.

In the case of using a daily point forecast as a period average forecast, we can appeal to the intermediate value theorem, since there always exists a point forecast equal to the period average. Ellwanger et al. (2023) show theoretically that a point forecast within a month converges to the monthly average as the persistence of the data increases, and at longer forecast horizons. For this reason, we explore a non-parametric approach which assumes proportionality. This approach is simple to construct, and empirically, it was shown to have predictive power for futures-based crude oil forecasts (Ellwanger and Snudden, 2023b). In addition to proportionality, we also explore methods to construct a point forecast equal to the period average by interpolating the futures forecasts from adjacent months.

In contrast to these non-parametric approaches, it is also possible to relax the theoretical assumption of proportionality and unbiasedness by adopting parametric approaches. Specifically, to accommodate the possibility that the spread could be a biased predictor of future average prices, we relax the assumption of a zero intercept in Equation 5 and accordingly estimate α. Moreover, the proportionality restriction can be relaxed and, accordingly, β can be estimated in that model. We also explore simultaneously relaxing both the unbiasedness and proportionality restrictions:

$$\hat{\bar{R}}_{t+h|t} = R_{t,n}\left(1 + \hat{\alpha} + \hat{\beta}\left(\ln F^{h,d}_{t,n} - \ln S_{t,n} - E_{t,n}\left(\pi^h_t\right)\right)\right), \;\; \forall\ h. \tag{6}$$

The parameters $\hat{\alpha}$ and $\hat{\beta}$ are obtained in real-time from recursive least-squares regressions estimates. The empirical evidence on the differences in forecast performance of all above-mentioned approaches are explored.

3.3 Forecast Evaluation

If commodity prices follow a random walk, by definition, the change in spot prices cannot be predicted. Specifically, suppose the daily price of a certain commodity follows a random walk, such that $R_{t,i}$, the real price on day i in month t, is given by the following equation:

$$R_{t,i} = R_{t,i-1} + \epsilon_{t,i}, \qquad \text{for } i = 1, 2, ..., n. \tag{7}$$

where n is the number of daily business-calendar real price observations within a month (about 21), $\epsilon_{t,i}$ is a mean-zero iid error term with variance σ^2_ϵ. The last observed price in month t is set on the last trading day, n $R_{t,n}$.

In this analysis, we aim to predict a commodity's monthly average real price h periods ahead. We can interpret the monthly average of nominal prices deflated by CPI equivalently as the monthly average of daily real prices:

$$\bar{R}_t \equiv \frac{\frac{1}{n}\sum_{i=1}^{n} S_{t,i}}{p_t} \equiv \frac{1}{n}\sum_{i=1}^{n}\frac{S_{t,i}}{p_t} \equiv \frac{1}{n}\sum_{i=1}^{n} R_{t,i}.$$

That is, the monthly average real price is the temporal aggregate of the daily real prices. The conditional expectation, $E_t(\bar{R}_{t+h})$, of the average price h periods ahead, given time t information is:

$$E_{t,n}(\bar{R}_{t+h}) = R_{t,n} \quad \forall\ h.$$

That, is if daily prices follow a random walk, only the last daily observation reflects the traditional random walk forecasts for all future values in levels, averaged or not. Moreover, Ellwanger and Snudden (2023a) show that if daily prices follow a random walk, then the monthly average no-change forecast, $\bar{R}_t$, produces strictly larger forecast errors than $R_{t,n}$ in theory.

Moreover, forecast improvements relative to the monthly average no-change forecast are expected for all autoregressive integrated moving average representations of the daily data (Weiss, 1984; Marcellino, 1999), including the special case where the daily real price follows a random walk. As such, companions against the monthly average no-change do not reflect the traditional random walk used in finance and could result in spurious predictability.

We empirically compare the forecasting accuracy of end-of-month compared to average price no-change for monthly average real prices for seventeen primary commodities. The empirical results, detailed in Table A.2, suggest that the end-of-month no-change is a much more stringent no-change benchmark than the period average no-change for all primary commodities considered, especially at shorter horizons. The end-of-month no-change improves upon the monthly average no-change by up to 48 percent for the MSPE ratio, and 52 percent improvements in directional accuracy. Both the magnitude and convergence of the forecasts at longer horizons, for both directional accuracy and mean-squared precision, reflect outcomes expected if a random walk closely approximated the daily data.

Thus, all forecasts herein are reported and tested against the end-of-month no-change forecast. This provides the first instance of futures-based forecasts of period average commodity prices being tested against the traditional random walk hypothesis. We employ two forecast evaluation criteria: the Mean Squared Forecast Error (MSFE) ratio and mean directional accuracy, termed success ratios. The MSFE ratio for the h-step-ahead forecast, $MSFE_h^{ratio}$, is computed as the quotient of the MSFE of the model-based forecast and the MSFE of the no-change benchmark. The formula is as follows:

$$MSFE_h^{ratio} = \frac{E[\sum_{q=1}^{Q}(\bar{R}_{q+h} - \hat{R}_{q+h|q})^2]}{E[\sum_{q=1}^{Q}(\bar{R}_{q+h} - R_{q,n|q})^2]}, \tag{8}$$

where $\hat{R}_{q+h|q}$ represents the model forecast for the h step ahead average price $\bar{R}_{q+h}$, and $R_{q,n}$ is the end-of-month no-change forecast for the evaluation sample $q = 1, 2, \ldots, Q$. The null hypothesis of equal MSFE of the model-based forecast relative to the no-change forecast, is tested following Diebold and Mariano (1995), constructed with Newey and West (1987) standard errors, and compared against standard normal critical values. Values of the MSPE ratio less than one denote improvements upon the end-of-period no-change forecast.

Directional accuracy is evaluated using the mean directional accuracy. This metric describes the fraction of times the forecast can correctly predict the change in the direction of the price of the commodity:

$$SR_h = \frac{1}{Q}\sum_{q=1}^{Q} \mathbb{1}\{sgn(\bar{R}_{q+h} - R_{q,n}) = sgn(\hat{R}_{q+h|q} - R_{q,n|q})\}, \tag{9}$$

where sgn is a sign function and $\mathbb{1}$ is an indicator function. The test statistic is calculated following Pesaran and Timmermann (2009). The null hypothesis is that the futures-based forecast has a 50 percent success rate in predicting the direction of change in the real price of the respective commodity. Therefore, a success ratio above 0.5 indicates an improvement over a random change in direction.

4 Real-Time Data

We examine seventeen commodity spot prices, across four major categories: energy (West Texas Intermediate (WTI) crude oil, Henry Hub natural gas, heating oil, RBOB gasoline, and ethanol), precious metals (gold, silver, and platinum), base metals (copper, aluminum, nickel, tin, lead, and zinc), and agricultural commodities (wheat, corn, and soybeans).

To construct real-time forecasts of real prices, the vintages of the seasonally adjusted U.S. consumer price index are obtained from the real-time database maintained by the Philadelphia Federal Reserve. The data begins in January 1973, and the historical average of CPI is used to generate the expected inflation to construct the real prices.

4.1 Data Sources

The daily commodity futures and spot data are sourced from Bloomberg, are available in real-time, and pertain to the daily closing prices. The exception is spot prices of crude and heating oil, which are obtained from the US Energy Information Administration. Table 3 lists the details of the futures contracts, including Bloomberg tickers, grades, and the start date of available futures contracts at different horizons (1-month, 12-months, and 24-months). Based on the contract specifications, Table 3 also provides details of the settlement dates, delivery period, and the months for which the contracts are actively traded.

The spot price series are chosen to ensure consistency with the futures contracts. First, the spot data correspond to the same trading exchange and delivery location as the futures data. For example, Cushing, Oklahoma, serves as the designated delivery location for crude oil, whereas Chicago is the delivery region for agricultural commodities, consistent with futures contracts that specify no price differentials at these locations. Second, the same grade of the commodity is used, which is particularly relevant for agricultural commodities.[3]

4.2 Alignment of Contracts with Horizons

Futures contracts are traded for every month up to several months ahead for energy and base metals. In contrast, only select months are traded for precious metals and agricultural commodities, see column "listed contracts" in Table 3. For example, wheat futures contracts are available for delivery in March, May, July, September, and December. To ensure a forecast can be constructed in every month of the forecast evaluation sample, we follow Chinn and Coibion (2014) and interpolate missing monthly values in the futures curve using the observed contracts. Specifically, the delivery dates of each contract are aligned with the closest corresponding monthly horizon. We then employ a linear interpolation of the missing data along the futures curve if values are missing at longer horizons. We find that alternative interpolation methods have almost no effect on forecast performance beyond the one-month ahead forecasts.

More important than the interpolation of missing contracts along the futures curve is the align-

[3] For example, both wheat spot and futures prices are No.2 Soft Red Winter. However, for soybeans, where the CBOT futures are for No.2 yellow soybeans with a 6-cent premium for No.1, we adjust the spot price of soybeans by subtracting 6 cents because the spot price is only available for No.1 yellow soybeans. Details of the spot prices are further detailed in appendix A.

Table 3. Bloomberg Tickers for Commodity Futures, Sample Periods, and Contract Details

Commodity	Exchange	Grade/Name	Ticker	Sample Start			Maximum		Listed Contracts	Settlement Date	Delivery Period
				1-month	12-month	24-month	Max	Start date			
Energy											
Crude oil	NYMEX	WTI	CL	1990.01	1990.01	1990.11	129	2019.11	Monthly	3BD before 25th of Jan.	First to last BD of Feb.
Natural Gas	NYMEX	Henry Hub	NG	1990.04	1990.06	1995.09	151	2008.02	Monthly	3rd Last BD of Jan.	First to last day of Feb.
Heating Oil	NYMEX	NY Harbor ULSD	HO	1990.01	1990.01	2007.04	44	2012.04	Monthly	Last BD of Dec.	From the 9th to the 30th of Jan.
Gasoline	NYMEX	RBOB	XB	2005.10	2005.10	2007.02	44	2015.11	Monthly	Last BD of Dec.	From the 9th to the 30th of Jan.
Ethanol	CBOT	ASTM D4806, CA	DL	2005.05	2005.08	2007.01	36	2008.02	Monthly	3rd BD of Jan.	From 1st BD of Jan. to 2nd BD post-settlement.
Precious Metals											
Gold	COMEX	Min of 995 fineness	GC	1990.01	1990.01	1990.01	72	1990.12	2,4,6,8,10,12	3rd Last BD of Feb.	First to last BD of Feb
Silver	COMEX	Min of 999 fineness	SI	1990.01	1990.01	1990.01	44	1993.07	3,5,7,9,12	3rd Last BD of Mar.	First to last BD of Mar
Platinium	NYMEX	Min of 99.95% pure	PL	1990.01	-	-	12	1990.01	1,4,7,10	3rd Last BD of Jan.	First to last BD of Jan
Base Metals											
Aluminum	LME	High grade primary	LA	1997.07	1997.07	1997.07	123	2008.09	Monthly	Tue before 3rd Wed of Jan	Two BD after settlment
Copper	LME	Grade A	LP	1997.06	1997.07	1997.07	123	2008.09	Monthly	Tue before 3rd Wed of Jan	Two BD after settlment
Lead	LME	Min of 99.97% purity	LL	1997.07	1997.10	2008.09	63	2008.09	Monthly	Tue before 3rd Wed of Jan	Two BD after settlment
Zinc	LME	Min of 99.97% purity	LX	1997.07	1997.07	1997.07	63	2008.09	Monthly	Tue before 3rd Wed of Jan	Two BD after settlment
Nickel	LME	Min of 99.80% purity	LN	1997.07	1997.07	1997.07	63	2008.09	Monthly	Tue before 3rd Wed of Jan	Two BD after settlment
Tin	LME	Min of 99.85% purity	LT	1997.07	1997.10	-	16	1998.01	Monthly	Tue before 3rd Wed of Jan	Two BD after settlment
Agricultural											
Corn	CBOT	No. 2 Yellow	C	1990.01	1990.01	1993.03	39	2006.09	3,5,7,9,12	BD Before 15th of Mar.	From Mar. 1st BD to 2nd BD post-settlement
Soybeans	CBOT	No. 2 Yellow	S	1990.01	1990.01	1993.01	40	2009.11	1,3,5,7,8,9,11	BD Before 15th of Jan	From Jan. 1st BD to 2nd BD post-settlement
Wheat	CBOT	No. 2 Soft Red Winter	W	1990.01	1990.01	1992.09	30	2000.09	3,5,7,9,12	BD Before 15th of Mar.	From Mar. 1st BD to 2nd BD post-settlement

Note: Exchange is the marketplace where each commodity's contract is listed. *Grade/Name* specifies the quality or type of the commodity being traded. *Ticker* is the Bloomberg ticker used for downloading the data. *Sample Start* indicates the starting month and year from which the data was used in the analysis. *Maximum horizon* represents the longest period, in months, over which the contract is available for trading. *Listed Contracts* refer to the trading frequency and contract months available. The numbers represent the months the contracts are listed, with $1 =$ January, $2 =$ February, ..., and $12 =$ December. *Settlement Date* is the date by which the contract must be settled or expire. *Delivery Period* is the time frame within which the physical delivery of the commodity is expected to occur. For further details, refer to the individual contract specifications from the corresponding exchange. The last two columns assume that the forecaster uses the front contract on the last business day (BD) of December, with examples given for heating oil and gasoline for the last business day of December 2024.

ment of the contracts with the forecast horizons. For base and precious metals, trading of the contract price observed on the last day of the month terminates in the third week of the contract month, with delivery occurring just two days after settlement. Thus, the delivery period of the front-month contract is the market's expectation for the one-month ahead. A similar situation arises for precious metals, where the settlement and delivery dates overlap within a month. However, the alignment of the contracts with the forecast horizon requires more careful consideration for the other commodities. Consider the crude oil futures market. The front contract observed at the end of each month is settled in the next month, three business days before the 25th, and corresponds with a delivery date two months ahead. For example, Figure 1b depicts that the front contact on December 31 is settled at the end of January (blue arrow) and corresponds with a February delivery (gray arrows). Following Ellwanger and Snudden (2023b), we align the front contract to the two-month ahead horizon and impute the one-step-ahead forecast using the curvature of the futures curve up to 12 contracts.

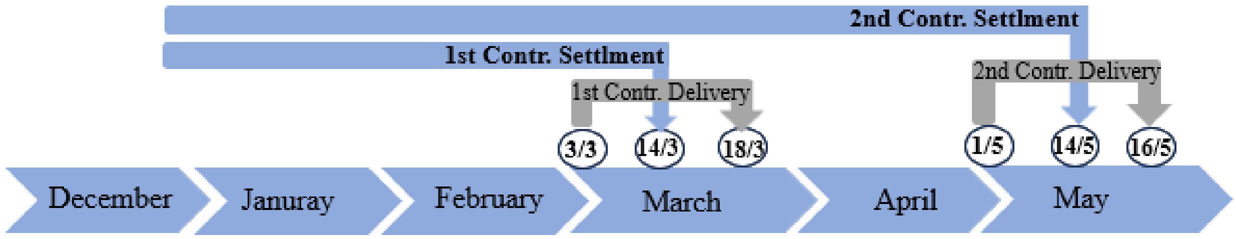
The contract specification for natural gas is similar to crude oil in that trading of the front-month contract terminates on the 3rd last business day of the month before the contract month, and delivery occurs during the next month. In this case, we also consider constructing the one-month ahead forecasts by averaging the spot price and the front-month contract (two-month forecast). As reported in appendix Table A.6 this method performs similarly to using the average curvature, and both methods substantially outperform alternative assumptions for the one-month ahead.

The front-month contract of other energy commodities, such as heating oil, settles at the end of the month, and delivery is at the beginning of the next month. This means that such contracts may experience reduced liquidity as the contract is at expiration and moves to physical delivery. Moreover, the beginning of the month delivery may mean that an accurate prediction of the monthly average can be constructed using a weighted average of the forecasts from the first and second contracts (see for example Ellwanger et al., 2023). To investigate this, we construct a one-month-ahead forecast using the average of the first and second contracts and compare this to the alternative of using an average of the current spot price and the second contract. We find that such assumptions reduce the one-month ahead mean-squared error by as much as 46 percent. For these commodities, the average of the spot and the second-month contract is used as the forecast for the month ahead.

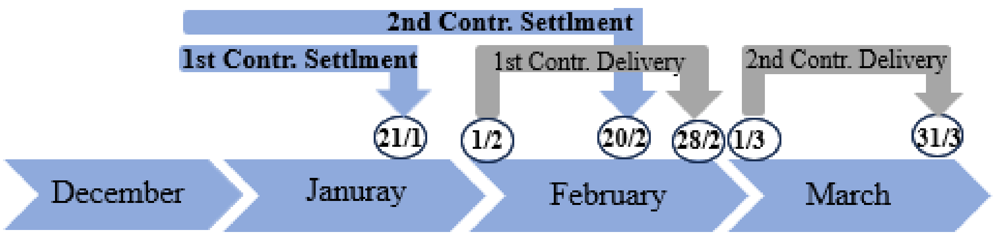
For agricultural commodities, again, delivery takes place at the beginning of the month. For example, the front contracts for wheat observed on December 31 would be scheduled for delivery between the 1st and 18th of March, see Figure 1a. We thus consider that an average of the current

Figure 1. Settlement and Delivery for Wheat and Crude oil on December 31

(a) Trading schedules of the first two futures contracts for wheat



(b) Trading schedules of the first two futures contracts for crude oil



Note: Settlement and delivery procedures for the two contracts of wheat and crude oil for a trade conducted on December 31, 2024. "Contr." refers to "Contract". Settlement dates mark the official end of the trading contract, while the delivery period is the period during which the physical commodity is scheduled to be delivered. Circled numbers indicate specific dates for settlement and delivery (formatted as dd/mm).

month and the preceding month's futures prices would be a better representation of the current monthly average spot price. We find that such calculation yields consistent, albeit small, gains in forecast performance one month ahead and use this as the baseline for the forecasts of agricultural commodities.

Note that these time alignment assumptions only affect the results of the one-month ahead forecast. For a detailed comparison for all proposed one-month ahead assumptions for the affected commodities, including outcomes using the front contract without time alignment considerations, see appendix Table A.6.

5 Results

Our baseline forecast evaluation sample begins in 2010 since this is when futures contracts at longer horizons became consistently available for all commodities (see Table 3). We also conduct robustness of the forecast performance over time and for specific events in section 5.6.

5.1 Non-Parametric Forecasts

Results for non-parametric futures-based forecasts of the monthly average real spot price, following equation 5, are reported in Table 4. These baseline results utilize end-of-month futures prices, and they are tested against the end-of-month no-change forecast. Results are shown for different monthly forecast horizons (1 month, 3 months, 6 months, etc). The top panel presents results for the mean squared forecast error (MSFE) ratio. An MSFE ratio of less than 1 indicates that the futures forecast outperformed the traditional random walk. P-values are shown in parentheses to test the null hypothesis of equal MSFEs. Results for the success ratio are presented in the bottom panel of Table 4 and provide the share of times that the futures-based forecasts corrected predicted the directional change in the real commodity price level. A success ratio above 0.5 indicates improvements upon random chance, and the p-value for the test of the null hypothesis of no directional accuracy is provided in brackets.

One month out, as shown by the success ratio, futures markets provide gains in directional accuracy for twelve of the seventeen commodities. These improvements are statistically significant at the 10 percent level for eight commodities. As the forecast horizon increases, improvements in directional accuracy are exhibited for more commodities. For example, at the one-year horizon, the success ratio exceeds 0.5 for fourteen of the seventeen commodities. Of these fourteen, directional accuracy gains are significant at the ten percent level for ten commodities. Two years out, the success ratio exceeds 0.5 for all commodities except gold. The magnitude of the directional accuracy gains at longer horizons is often substantive, with platinum showing correct directional accuracy 84 percent of the time.

Similar gains are achieved for forecasts in terms of mean-squared precision. Gains in the MSPE ratio for the majority of commodities are found at the three-month horizons and beyond. Beyond one-year ahead, futures-based forecasts provide precision gains for all commodity markets. Moreover, the magnitudes are substantial for some markets. For example, substantial horizon gains are observed for ethanol, gasoline, and soybeans. At one year ahead, double-digit gains in mean squared precision are found for the majority of the energy and agricultural market. Nickel, lead, and copper show improvements at the two-year horizon, with gains of 20, 19, and 12 percent respectively.

Table 4. Futures-based Forecasts of Monthly Real Prices, Non-Parametric

	1	3	6	9	12	15	18	21	24
Commodity					MSFE Ratio				
Crude Oil	0.99 (0.313)	0.94 (0.021)	0.88 (0.037)	0.86 (0.066)	0.82 (0.054)	0.77 (0.022)	0.71 (0.012)	0.66 (0.007)	0.61 (0.003)
Natural Gas	1.02 (0.663)	1.01 (0.532)	0.97 (0.387)	1.07 (0.665)	1.07 (0.672)	0.97 (0.395)	0.97 (0.396)	0.97 (0.394)	0.97 (0.419)
Heating Oil	1.04 (0.767)	0.98 (0.340)	0.96 (0.251)	0.91 (0.038)	0.87 (0.005)	0.85 (0.001)	0.82 (0.000)	0.78 (0.000)	0.74 (0.000)
Gasoline	0.81 (0.004)	0.75 (0.002)	0.69 (0.004)	0.81 (0.041)	0.88 (0.078)	0.81 (0.023)	0.74 (0.009)	0.73 (0.008)	0.69 (0.002)
Ethanol	0.72 (0.125)	0.74 (0.120)	0.84 (0.233)	0.83 (0.174)	0.77 (0.118)	0.71 (0.048)	0.68 (0.042)	0.63 (0.041)	0.59 (0.027)
Gold	1.01 (0.607)	1.00 (0.426)	1.00 (0.510)	0.99 (0.404)	0.98 (0.344)	0.97 (0.286)	0.96 (0.225)	0.95 (0.159)	0.93 (0.118)
Silver	1.04 (0.885)	1.00 (0.495)	0.99 (0.288)	0.98 (0.157)	0.97 (0.124)	0.96 (0.076)	0.93 (0.029)	0.89 (0.018)	0.87 (0.016)
Platinum	1.02 (0.860)	0.98 (0.067)	0.93 (0.008)	0.91 (0.010)	0.89 (0.009)	0.88 (0.001)	0.86 (0.000)	0.85 (0.000)	0.85 (0.000)
Aluminum	1.00 (0.527)	1.01 (0.647)	0.98 (0.250)	0.95 (0.118)	0.96 (0.077)	0.96 (0.105)	0.97 (0.157)	0.97 (0.191)	0.96 (0.172)
Copper	0.98 (0.042)	0.98 (0.170)	0.97 (0.118)	0.94 (0.086)	0.93 (0.072)	0.92 (0.061)	0.90 (0.040)	0.88 (0.037)	0.88 (0.057)
Lead	0.97 (0.036)	0.97 (0.008)	0.93 (0.008)	0.87 (0.010)	0.86 (0.010)	0.85 (0.022)	0.84 (0.030)	0.83 (0.013)	0.81 (0.010)
Zinc	0.97 (0.097)	0.95 (0.083)	0.93 (0.081)	0.89 (0.028)	0.90 (0.049)	0.91 (0.089)	0.92 (0.121)	0.92 (0.162)	0.93 (0.233)
Nickel	1.00 (0.633)	1.00 (0.529)	0.97 (0.143)	0.95 (0.106)	0.94 (0.097)	0.89 (0.046)	0.85 (0.022)	0.82 (0.011)	0.80 (0.007)
Tin	1.00 (0.508)	1.03 (0.697)	1.02 (0.623)	1.01 (0.526)	0.98 (0.424)	0.95 (0.226)	0.95 (0.189)	0.98 (0.338)	0.99 (0.442)
Corn	1.03 (0.580)	0.75 (0.054)	0.67 (0.031)	0.70 (0.046)	0.71 (0.051)	0.67 (0.036)	0.63 (0.033)	0.61 (0.028)	0.57 (0.012)
Soybeans	0.86 (0.125)	0.77 (0.039)	0.73 (0.032)	0.78 (0.052)	0.84 (0.148)	0.77 (0.121)	0.72 (0.080)	0.72 (0.070)	0.67 (0.032)
Wheat	1.10 (0.911)	1.06 (0.761)	1.02 (0.565)	0.98 (0.456)	0.96 (0.414)	0.96 (0.386)	0.94 (0.292)	0.93 (0.222)	0.89 (0.166)
					Success Ratio				
Crude Oil	0.55 (0.091)	0.52 (0.208)	0.58 (0.093)	0.62 (0.031)	0.68 (0.002)	0.69 (0.000)	0.66 (0.002)	0.64 (0.005)	0.75 (0.000)
Natural Gas	0.52 (0.321)	0.54 (0.169)	0.61 (0.000)	0.63 (0.004)	0.64 (0.006)	0.66 (0.003)	0.63 (0.017)	0.64 (0.006)	0.62 (0.021)
Heating Oil	0.52 (0.300)	0.56 (0.072)	0.61 (0.019)	0.69 (0.000)	0.77 (0.000)	0.82 (0.000)	0.81 (0.000)	0.83 (0.000)	0.81 (0.000)
Gasoline	0.62 (0.001)	0.62 (0.004)	0.71 (0.000)	0.65 (0.001)	0.62 (0.001)	0.62 (0.001)	0.65 (0.002)	0.69 (0.000)	0.70 (0.000)
Ethanol	0.55 (0.086)	0.59 (0.015)	0.66 (0.000)	0.64 (0.001)	0.64 (0.024)	0.69 (0.000)	0.64 (0.001)	0.68 (0.000)	0.73 (0.000)
Gold	0.47 (0.444)	0.55 (0.114)	0.48 (0.170)	0.54 (0.140)	0.52 (0.616)	0.57 (0.000)	0.55 (0.000)	0.56 (0.000)	0.50 (0.000)
Silver	0.47 (0.753)	0.50 (0.779)	0.59 (0.353)	0.66 (0.069)	0.67 (0.037)	0.66 (0.004)	0.67 (0.000)	0.67 (0.000)	0.63 (0.009)
Platinum	0.49 (0.370)	0.56 (0.238)	0.66 (0.016)	0.64 (0.114)	0.72 (0.011)	0.76 (0.002)	0.79 (0.000)	0.82 (0.000)	0.84 (0.000)
Aluminum	0.47 (0.702)	0.45 (0.862)	0.46 (0.682)	0.47 (0.598)	0.50 (0.466)	0.49 (0.504)	0.53 (0.235)	0.56 (0.061)	0.56 (0.064)
Copper	0.53 (0.024)	0.53 (0.000)	0.60 (1.000)	0.61 (1.000)	0.63 (1.000)	0.63 (1.000)	0.60 (1.000)	0.59 (1.000)	0.59 (1.000)
Lead	0.56 (0.060)	0.61 (0.005)	0.60 (0.057)	0.62 (0.020)	0.58 (0.011)	0.65 (0.009)	0.66 (0.144)	0.65 (0.080)	0.67 (0.061)
Zinc	0.53 (0.519)	0.50 (0.548)	0.52 (0.346)	0.51 (0.344)	0.57 (0.086)	0.61 (0.021)	0.60 (0.020)	0.59 (0.012)	0.58 (0.120)
Nickel	0.50 (1.000)	0.49 (0.790)	0.50 (0.569)	0.50 (1.000)	0.50 (1.000)	0.50 (1.000)	0.49 (1.000)	0.56 (0.000)	0.55 (0.000)
Tin	0.53 (1.000)	0.50 (1.000)	0.48 (1.000)	0.52 (1.000)	0.52 (1.000)	0.54 (1.000)	0.58 (1.000)	0.57 (1.000)	0.54 (1.000)
Corn	0.56 (0.028)	0.63 (0.001)	0.64 (0.004)	0.57 (0.110)	0.51 (0.444)	0.52 (0.355)	0.55 (0.177)	0.56 (0.093)	0.59 (0.024)
Soybeans	0.56 (0.051)	0.53 (0.260)	0.60 (0.021)	0.63 (0.012)	0.58 (0.074)	0.58 (0.150)	0.55 (0.144)	0.58 (0.087)	0.62 (0.004)
Wheat	0.55 (0.088)	0.56 (0.075)	0.58 (0.034)	0.49 (0.840)	0.48 (0.881)	0.49 (0.733)	0.53 (0.441)	0.54 (0.485)	0.55 (0.371)

Notes: Futures-based forecasts of monthly average spot prices by the end-of-month futures prices, January 2010–2023. The values in the brackets are the p-values for the null hypothesis of equal MSFE ratios based on the DM-test (Diebold and Mariano, 1995) and the null of no accuracy of changing direction relative to the random walk, no-change forecast based on Pesaran and Timmermann (2009).

For robustness, we consider how the use of direct forecasts influences estimates, see equation 4. These forecasts eliminate the log approximations used in the baseline spread model, equation 5. The results are shown in appendix Table A.5. For the direct forecasts, out of the 153 MSFE ratios, only 17 (or approximately 11%) are less than the values presented in the baseline results in Table 4. Additionally, we do not find any improvements over the baseline results in terms of directional accuracy. Moreover, any differences are economically insignificant. This finding shows that utilizing the actual futures price is nearly equally useful in practice.

We also test for seasonality in the forecast errors from the forecasts reported in Table 4. Specifically, we regress the forecast errors on monthly dummies and test the joint significance of the coefficients, see appendix Table A.7. We do not find evidence of seasonality in forecast errors for the alternative commodities and forecast horizons, except for tin and platinum at short horizons.[4]

Overall, the results suggest that non-parametric approaches that utilize the latest expectations of futures markets provide predictive power for monthly average real spot prices across a broad range of commodities and time horizons. These results demonstrate predictive gains for monthly average prices relative to the traditional random walk forecast for most primary commodities, particularly over medium- and long-term horizons. These findings for period average prices are consistent with the results obtained for nominal point-sampled returns of primary commodities by Chinn and Coibion (2014) and Reeve and Vigfusson (2011).

5.2 Effects of Averaging Futures

We next investigate whether averaging futures prices over the month affects forecast performance, a technique utilized in several prior studies (see, e.g., Baumeister and Kilian, 2012; Alquist et al., 2013; Drachal, 2016; Chu et al., 2022). The results are shown in Table 5 with bolded values indicating whether the MSFE ratio and success ratio improve upon the baseline results in Table 4.

The results show less forecast precision, especially for short-term horizons when averaging futures prices, particularly evident at the one-month horizon. For example, the MSFE ratio is over 50 percent larger for energy commodities one month ahead. Only for silver are there MSFE gains at the one-month ahead from averaging, although they are statistically insignificant. Consistent with theory, the effects of averaging on forecast accuracy are less pronounced at longer horizons. At the one-year horizon and beyond, both methods yield similar predictive effectiveness, although end-of-month futures generally provide slight advantages for most commodities. This suggests that while averaging futures prices could still offer long-term predictive value, opting for end-of-month futures data is preferable for short-term forecast accuracy.

Differences in directional accuracy, measured by the Success Ratio (SR), do not mirror the magnitude in the decline seen with MSPE across all commodities at short horizons. In fact, averaging slightly improves the SR for a few commodities, notably lead, copper, and wheat. This highlights differences between the two forecast evaluation criteria, as the success ratio is invariant to the magnitude of the forecast error. That said, end-of-month futures data, instead of averaging, continues to enhance forecast directional accuracy for most commodities and horizons.

[4]Note that even if seasonality in forecast errors were found to be present, (i.e. Hevia et al., 2018), consistent with (i.e. Baumeister et al., 2017) we do not find evidence that real-time estimates of the seasonality improve forecast accuracy.

Table 5. Futures-based Forecasts of Monthly Real Prices, Non-Parametric, Monthly Average Futures

	1	3	6	9	12	15	18	21	24
Commodity					MSFE Ratio				
Crude Oil	1.82 (1.000)	1.00 (0.514)	0.89 (0.040)	0.87 (0.102)	0.83 (0.074)	0.77 (0.028)	0.71 (0.013)	0.66 (0.007)	0.61 (0.003)
Natural Gas	1.56 (0.999)	1.03 (0.653)	1.06 (0.708)	1.13 (0.763)	1.11 (0.742)	1.01 (0.541)	1.01 (0.539)	0.99 (0.467)	0.99 (0.463)
Heating Oil	1.74 (0.999)	1.08 (0.860)	1.00 (0.477)	0.94 (0.133)	0.88 (0.015)	0.86 (0.005)	0.83 (0.001)	0.79 (0.001)	0.74 (0.000)
Gasoline	1.33 (0.967)	0.81 (0.012)	0.70 (0.004)	0.82 (0.053)	0.89 (0.101)	0.82 (0.033)	0.75 (0.012)	0.73 (0.008)	0.69 (0.002)
Ethanol	1.32 (0.772)	0.75 (0.123)	**0.83 (0.227)**	**0.81 (0.154)**	**0.75 (0.109)**	**0.69 (0.049)**	**0.66 (0.042)**	**0.61 (0.037)**	**0.57 (0.025)**
Gold	1.24 (0.992)	1.05 (0.884)	1.06 (0.893)	1.01 (0.552)	1.01 (0.553)	0.99 (0.432)	0.98 (0.378)	0.97 (0.270)	0.93 (0.134)
Silver	**0.96 (0.445)**	1.03 (0.649)	1.00 (0.507)	0.98 (0.371)	**0.96 (0.258)**	**0.93 (0.116)**	**0.92 (0.066)**	0.89 (0.041)	0.88 (0.049)
Platinum	1.42 (0.998)	1.04 (0.799)	0.95 (0.160)	0.92 (0.043)	0.90 (0.027)	**0.87 (0.002)**	0.88 (0.001)	0.88 (0.000)	0.88 (0.000)
Aluminum	1.72 (0.995)	1.08 (0.897)	1.01 (0.534)	0.95 (0.215)	0.96 (0.127)	**0.93 (0.048)**	**0.94 (0.079)**	**0.95 (0.119)**	**0.93 (0.114)**
Copper	1.56 (1.000)	1.08 (0.865)	1.01 (0.566)	0.97 (0.316)	0.95 (0.202)	**0.91 (0.068)**	**0.89 (0.048)**	0.88 (0.048)	**0.87 (0.056)**
Lead	1.42 (0.995)	0.98 (0.378)	0.96 (0.238)	0.88 (0.040)	**0.85 (0.024)**	**0.82 (0.015)**	**0.81 (0.018)**	**0.82 (0.016)**	**0.79 (0.007)**
Zinc	1.74 (0.999)	1.05 (0.795)	0.96 (0.294)	0.89 (0.069)	0.90 (0.105)	0.91 (0.129)	0.93 (0.182)	0.94 (0.251)	0.94 (0.255)
Nickel	1.51 (0.998)	1.09 (0.913)	1.00 (0.448)	0.97 (0.338)	0.96 (0.299)	**0.88 (0.068)**	**0.84 (0.040)**	**0.81 (0.019)**	**0.79 (0.011)**
Tin	1.82 (0.999)	1.20 (0.989)	1.06 (0.764)	1.02 (0.559)	1.00 (0.483)	**0.94 (0.227)**	**0.93 (0.170)**	**0.96 (0.227)**	**0.97 (0.223)**
Corn	1.16 (0.763)	0.86 (0.111)	0.73 (0.035)	0.73 (0.052)	0.75 (0.063)	0.68 (0.036)	0.64 (0.033)	0.62 (0.028)	0.58 (0.014)
Soybeans	1.48 (0.997)	0.84 (0.081)	0.76 (0.043)	0.79 (0.055)	**0.83 (0.144)**	0.77 (0.119)	0.73 (0.088)	0.73 (0.078)	0.68 (0.035)
Wheat	1.71 (0.980)	1.14 (0.842)	1.08 (0.710)	0.98 (0.457)	**0.94 (0.361)**	**0.92 (0.297)**	**0.93 (0.258)**	0.93 (0.229)	**0.88 (0.174)**
					Success Ratio				
Crude Oil	0.46 (0.821)	0.50 (0.408)	0.58 (0.029)	0.60 (0.021)	0.63 (0.002)	0.68 (0.000)	0.62 (0.009)	0.62 (0.008)	0.72 (0.000)
Natural Gas	0.52 (0.308)	0.50 (0.500)	0.58 (0.017)	0.61 (0.010)	0.64 (0.005)	0.64 (0.005)	0.63 (0.011)	0.63 (0.010)	0.62 (0.017)
Heating Oil	0.50 (0.518)	0.55 (0.184)	0.60 (0.015)	0.65 (0.004)	0.75 (0.000)	0.79 (0.000)	0.80 (0.000)	0.79 (0.000)	0.77 (0.000)
Gasoline	0.59 (0.008)	**0.65 (0.000)**	0.68 (0.000)	0.62 (0.011)	**0.64 (0.000)**	0.62 (0.002)	0.61 (0.012)	0.68 (0.000)	0.67 (0.000)
Ethanol	0.52 (0.328)	0.59 (0.021)	0.64 (0.000)	0.62 (0.007)	0.64 (0.020)	**0.70 (0.000)**	**0.65 (0.000)**	0.68 (0.000)	0.72 (0.000)
Gold	**0.53 (0.233)**	0.53 (0.242)	0.46 (0.765)	**0.55 (0.149)**	**0.55 (0.205)**	0.54 (0.294)	0.54 (0.129)	0.56 (0.053)	0.49 (0.134)
Silver	**0.54 (0.158)**	**0.58 (0.032)**	0.56 (0.093)	0.56 (0.142)	0.51 (0.680)	0.55 (0.342)	0.57 (0.184)	0.57 (0.148)	0.58 (0.111)
Platinum	0.49 (0.616)	0.56 (0.061)	0.58 (0.081)	0.60 (0.031)	0.63 (0.024)	0.66 (0.001)	0.61 (0.086)	0.63 (0.070)	0.59 (0.479)
Aluminum	**0.53 (0.280)**	**0.52 (0.290)**	0.50 (0.479)	**0.56 (0.100)**	**0.55 (0.138)**	**0.51 (0.343)**	0.53 (0.194)	**0.57 (0.056)**	0.56 (0.050)
Copper	**0.62 (0.001)**	0.53 (0.240)	0.58 (0.191)	0.57 (0.402)	0.56 (0.801)	0.60 (0.443)	0.59 (0.356)	0.58 (0.383)	**0.60 (0.095)**
Lead	**0.59 (0.010)**	0.53 (0.272)	0.58 (0.021)	0.62 (0.002)	0.57 (0.046)	0.62 (0.012)	0.65 (0.026)	**0.68 (0.002)**	0.66 (0.031)
Zinc	0.52 (0.480)	**0.53 (0.268)**	**0.58 (0.029)**	**0.60 (0.007)**	**0.64 (0.000)**	**0.68 (0.000)**	**0.68 (0.000)**	**0.60 (0.004)**	0.58 (0.108)
Nickel	**0.53 (0.219)**	0.46 (0.841)	0.48 (0.659)	**0.55 (0.117)**	**0.55 (0.094)**	**0.57 (0.037)**	**0.60 (0.007)**	**0.59 (0.063)**	**0.62 (0.005)**
Tin	0.47 (0.785)	0.45 (0.905)	**0.52 (0.240)**	0.52 (0.398)	**0.61 (0.000)**	**0.61 (0.000)**	**0.61 (0.042)**	**0.60 (0.040)**	**0.59 (0.029)**
Corn	**0.58 (0.008)**	0.62 (0.001)	**0.66 (0.001)**	**0.61 (0.017)**	**0.54 (0.285)**	**0.54 (0.264)**	**0.58 (0.076)**	**0.59 (0.023)**	0.58 (0.029)
Soybeans	0.53 (0.234)	**0.55 (0.137)**	**0.63 (0.002)**	**0.64 (0.005)**	**0.61 (0.010)**	0.57 (0.166)	**0.58 (0.037)**	**0.61 (0.022)**	**0.63 (0.003)**
Wheat	**0.58 (0.023)**	**0.61 (0.007)**	**0.59 (0.019)**	**0.55 (0.248)**	**0.52 (0.527)**	0.50 (0.562)	0.53 (0.426)	**0.55 (0.334)**	**0.56 (0.274)**

Notes: Futures-based forecasts of monthly average spot prices by the monthly average futures prices January 2010–2023 Bold values represent improvements over the baseline results in Table 4. The values in the brackets are the p-values for the null hypothesis of equal MSFE ratios based on the DM-test (Diebold and Mariano, 1995) and the null hypothesis of no accuracy of changing direction relative to the random walk, no-change forecast based on Pesaran and Timmermann (2009).

We also examined futures curves constructed from the average prices of the last five trading days of each month, as detailed in appendix Table A.3. While this approach still resulted in a decrease in short-term MSFE precision compared to using only end-of-month prices, the reduction was generally smaller than with full-month averages. Any observed improvements over the baseline approach were marginal. These findings reinforce our primary recommendation to construct futures curves based on the most recent market expectations in lieu of averaging over multiple days.

5.3 Parametric Forecasts

The results of the prior two sections have used non-parametric methods to construct forecasts. Next, we utilize real-time parametric estimates using equation 6 and compare with the more simplistic non-parametric results. These forecasts estimate $\hat{\beta}$, thereby relaxing the proportionality assumption, and set $\hat{\alpha}$ to zero. Results are presented in Table 6. Additionally, we explore two other scenarios: one where $\hat{\beta}$ is set to zero and estimate $\hat{\alpha}$, and another where both $\hat{\alpha}$ and $\hat{\beta}$ are estimated simultaneously. The later two cases do not produce improvements in precision of forecasts relative to simply estimating $\hat{\beta}$. For brevity, detailed results of these latter two forecasts are provided in appendix Tables A.8 and A.9.

Table 6. Futures-based Forecasts of Monthly Real Prices, Parametric

	1	3	6	9	12	15	18	21	24
Commodity					MSFE Ratio				
Crude Oil	1.00 (0.147)	1.00 (0.009)	0.98 (0.014)	0.97 (0.029)	0.95 (0.027)	0.91 (0.010)	0.88 (0.007)	0.85 (0.004)	0.82 (0.002)
Natural Gas	1.00 (0.166)	**0.97 (0.036)**	**0.95 (0.190)**	1.00 (0.515)	1.06 (0.684)	1.03 (0.582)	1.07 (0.662)	1.10 (0.710)	1.12 (0.738)
Heating Oil	1.00 (0.184)	0.99 (0.096)	0.99 (0.037)	0.98 (0.009)	0.96 (0.003)	0.94 (0.001)	0.92 (0.000)	0.90 (0.000)	0.86 (0.000)
Gasoline	0.98 (0.004)	0.82 (0.001)	0.75 (0.014)	0.82 (0.047)	0.90 (0.104)	0.87 (0.137)	0.81 (0.140)	0.80 (0.134)	0.71 (0.040)
Ethanol	0.87 (0.036)	**0.69 (0.021)**	0.98 (0.481)	1.29 (0.754)	0.90 (0.369)	**0.69 (0.087)**	**0.65 (0.055)**	0.63 (0.045)	0.81 (0.115)
Gold	1.00 (0.644)	1.00 (0.333)	1.00 (0.124)	1.00 (0.049)	1.00 (0.010)	1.00 (0.001)	1.00 (0.001)	1.00 (0.002)	0.99 (0.007)
Silver	1.00 (0.375)	1.00 (0.178)	1.00 (0.048)	1.00 (0.017)	1.00 (0.022)	1.00 (0.017)	0.99 (0.007)	0.98 (0.006)	0.98 (0.007)
Platinum	1.00 (0.718)	1.00 (0.011)	1.00 (0.001)	1.00 (0.000)	1.00 (0.000)	0.99 (0.000)	0.99 (0.000)	0.99 (0.000)	0.98 (0.000)
Aluminum	1.00 (0.751)	1.00 (0.700)	1.00 (0.238)	1.00 (0.092)	1.00 (0.073)	1.00 (0.166)	1.00 (0.273)	1.00 (0.354)	1.00 (0.361)
Copper	1.00 (0.950)	1.00 (0.048)	1.00 (0.042)	0.99 (0.029)	0.98 (0.019)	0.97 (0.019)	0.96 (0.015)	0.95 (0.019)	0.93 (0.033)
Lead	1.00 (0.995)	1.00 (0.001)	0.99 (0.006)	0.97 (0.008)	0.96 (0.007)	0.94 (0.017)	0.92 (0.024)	0.89 (0.010)	0.86 (0.007)
Zinc	1.00 (0.971)	1.00 (0.043)	0.99 (0.043)	0.98 (0.016)	0.97 (0.029)	0.96 (0.052)	0.95 (0.069)	0.93 (0.099)	0.93 (0.161)
Nickel	1.00 (0.283)	1.00 (0.304)	0.99 (0.094)	0.97 (0.079)	**0.93 (0.067)**	**0.84 (0.037)**	**0.76 (0.020)**	**0.71 (0.010)**	**0.69 (0.007)**
Tin	1.00 (0.228)	1.00 (0.577)	1.00 (0.512)	1.00 (0.413)	0.99 (0.302)	0.98 (0.154)	0.97 (0.131)	0.98 (0.208)	0.99 (0.284)
Corn	1.00 (0.090)	0.98 (0.014)	0.95 (0.015)	0.95 (0.027)	0.94 (0.030)	0.90 (0.017)	0.85 (0.011)	0.81 (0.011)	0.77 (0.008)
Soybeans	1.00 (0.022)	0.98 (0.016)	0.95 (0.017)	0.93 (0.011)	0.91 (0.018)	0.87 (0.017)	0.84 (0.012)	0.82 (0.013)	0.78 (0.011)
Wheat	1.00 (0.086)	1.00 (0.210)	**0.99 (0.234)**	0.99 (0.203)	0.97 (0.138)	**0.95 (0.086)**	0.94 (0.030)	0.93 (0.018)	0.91 (0.037)
					Success Ratio				
Crude Oil	0.55 (0.091)	0.52 (0.208)	0.58 (0.093)	0.62 (0.031)	0.68 (0.002)	0.69 (0.000)	0.66 (0.002)	0.64 (0.005)	0.75 (0.000)
Natural Gas	0.52 (0.321)	0.54 (0.169)	0.61 (0.000)	0.63 (0.004)	0.64 (0.006)	0.66 (0.003)	0.63 (0.017)	0.64 (0.006)	0.62 (0.021)
Heating Oil	0.52 (0.300)	0.56 (0.072)	0.61 (0.019)	0.69 (0.000)	0.77 (0.000)	0.82 (0.000)	0.81 (0.000)	0.83 (0.000)	0.81 (0.000)
Gasoline	0.62 (0.001)	0.62 (0.004)	0.71 (0.000)	0.65 (0.001)	0.62 (0.001)	0.62 (0.001)	0.65 (0.002)	0.69 (0.000)	0.70 (0.000)
Ethanol	0.54 (0.207)	**0.60 (0.024)**	**0.68 (0.000)**	**0.65 (0.008)**	0.63 (0.129)	0.67 (0.000)	0.62 (0.024)	0.67 (0.002)	0.73 (0.000)
Gold	**0.53 (0.556)**	0.47 (0.630)	**0.52 (0.422)**	0.49 (0.570)	**0.58 (0.155)**	**0.70 (0.000)**	**0.67 (0.000)**	**0.65 (0.000)**	0.50 (0.000)
Silver	0.49 (0.535)	0.50 (0.779)	0.59 (0.353)	0.66 (0.069)	0.67 (0.037)	0.66 (0.004)	0.67 (0.000)	0.67 (0.000)	0.63 (0.009)
Platinum	0.49 (0.370)	0.56 (0.238)	0.66 (0.016)	0.64 (0.114)	0.72 (0.011)	0.76 (0.002)	0.79 (0.000)	0.82 (0.000)	0.84 (0.000)
Aluminum	**0.53 (0.351)**	**0.55 (0.138)**	0.46 (0.682)	0.47 (0.598)	0.50 (0.466)	0.49 (0.504)	0.53 (0.235)	0.56 (0.061)	0.56 (0.064)
Copper	0.47 (0.976)	0.53 (0.000)	0.60 (1.000)	0.61 (1.000)	0.63 (1.000)	0.63 (1.000)	0.60 (1.000)	0.59 (1.000)	0.59 (1.000)
Lead	0.44 (0.940)	0.61 (0.005)	0.60 (0.057)	0.62 (0.020)	0.58 (0.011)	0.65 (0.009)	0.66 (0.144)	0.65 (0.080)	0.67 (0.061)
Zinc	0.46 (0.547)	**0.51 (0.506)**	0.52 (0.346)	0.51 (0.344)	0.57 (0.086)	0.61 (0.021)	0.60 (0.020)	0.59 (0.012)	0.58 (0.120)
Nickel	0.50 (1.000)	0.49 (0.290)	0.50 (0.569)	0.50 (0.500)	0.50 (1.000)	0.50 (1.000)	0.49 (1.000)	0.56 (0.000)	0.55 (0.000)
Tin	0.53 (1.000)	0.50 (1.000)	0.48 (1.000)	0.52 (1.000)	0.52 (1.000)	0.54 (1.000)	0.58 (1.000)	0.57 (1.000)	0.54 (1.000)
Corn	0.55 (0.127)	**0.64 (0.000)**	**0.65 (0.001)**	**0.58 (0.066)**	**0.52 (0.404)**	0.50 (0.486)	0.55 (0.177)	0.56 (0.093)	0.58 (0.035)
Soybeans	0.55 (0.147)	0.53 (0.251)	0.60 (0.023)	0.63 (0.012)	0.57 (0.091)	0.58 (0.150)	**0.56 (0.117)**	0.58 (0.087)	0.61 (0.034)
Wheat	0.55 (0.069)	**0.57 (0.057)**	0.58 (0.033)	**0.51 (0.622)**	0.50 (0.774)	0.49 (0.659)	0.53 (0.441)	0.53 (0.536)	**0.56 (0.269)**

Notes: Forecast performance of forecasting regressions using the futures-spot spread model, by estimating β in equation 6 and keeping the constant as zero, January 2010–2023. MSFE ratios are expressed relative to the end-of-month no-change forecast. The bold values represent improvements over the baseline results in Table 4. The values in the brackets are the p-values for the null hypothesis of equal MSFE ratios based on the DM-test (Diebold and Mariano, 1995).

The parametric forecasts are both more complex to estimate and also generally result in worse performance compared to the non-parametric approach. While there are isolated instances where parametric estimates marginally outperform, these differences are small and inconsistent across forecast horizons. A notable exception is observed in the directional accuracy for gold, which sees improvement at the 15 to 21-month horizons, although this improvement does not extend to other horizons or to MSFE precision. Forecasts that relax the proportionality assumption for nickel show a consistent improvement in MSFE at 18 months and beyond, yet, these gains do not persist across other horizons or in terms of directional accuracy. We recommend forecasters utilize the more simplistic non-parametric approach, as these results do not suggest that the parametric approach produces consistent gains in forecast accuracy.

5.4 Nominal Forecasts

We now consider forecasts of nominal monthly average spot prices, Table 7. This exercise isolates the importance of the observed measure of inflation, including for both the real-time nowcast and forecast. Monthly average h-step ahead nominal futures-based spread forecasts are constructed as follows:

$$\hat{S}_{t+h,d|t} = S_{t,n}\left(1 + \ln(F_{t,n}^{h,d}/S_{t,n})\right), \tag{10}$$

This is similar to the baseline spread model for real forecasts, the equation 5, but uses the nominal spot price, $S_{t,n}$, and abstracts from inflation.

The MSFE performance of nominal forecasts is broadly consistent with the baseline findings, with only minor improvements in accuracy relative to forecasting real prices. Small gains in forecast directional accuracy relative to real forecasts are observed in some cases, especially at horizons of three months and beyond. In some cases, by two years, the differences in directional accuracy are more noticeable, in particular for gasoline, nickel, and soybeans. However, such forecast gains are not reflected in the MSFE ratio.

That said, a notable exception is that nominal gold prices now exhibit predictability, in stark contrast to that for real gold prices. Specifically, the forecasts for the nominal monthly average price of gold exhibit directional and mean-squared precision gains around the one-year horizon. This is likely due to the unique position that gold plays as a hedge against inflation. This is an interesting example of the unique characteristics that differentiate the commodity markets.

Table 7. Futures-based Forecasts of Monthly Average Nominal Prices, Non-Parametric

	1	3	6	9	12	15	18	21	24
Commodity					MSFE Ratio				
Crude Oil	**0.98 (0.232)**	0.95 (0.038)	0.91 (0.051)	0.90 (0.092)	0.88 (0.068)	0.84 (0.019)	0.79 (0.006)	0.75 (0.002)	0.71 (0.001)
Natural Gas	1.03 (0.690)	1.04 (0.723)	0.98 (0.437)	1.10 (0.716)	1.09 (0.717)	0.99 (0.447)	0.97 (0.394)	0.97 (0.402)	0.98 (0.431)
Heating Oil	1.04 (0.739)	**0.97 (0.302)**	0.98 (0.336)	0.93 (0.076)	0.89 (0.014)	0.88 (0.007)	0.86 (0.004)	0.85 (0.003)	0.81 (0.002)
Gasoline	0.82 (0.003)	0.76 (0.003)	0.72 (0.005)	0.85 (0.041)	0.91 (0.084)	0.86 (0.013)	0.79 (0.003)	0.79 (0.002)	0.77 (0.000)
Ethanol	0.78 (0.194)	0.76 (0.121)	0.87 (0.265)	0.84 (0.149)	0.78 (0.100)	0.72 (0.033)	0.71 (0.026)	0.67 (0.022)	0.65 (0.015)
Gold	**0.99 (0.240)**	**0.98 (0.137)**	**0.98 (0.193)**	**0.96 (0.060)**	**0.95 (0.037)**	**0.94 (0.035)**	**0.93 (0.031)**	**0.92 (0.030)**	**0.91 (0.037)**
Silver	1.05 (0.889)	1.01 (0.635)	1.00 (0.577)	1.00 (0.367)	1.00 (0.356)	1.00 (0.370)	0.99 (0.269)	0.99 (0.190)	0.98 (0.124)
Platinum	1.02 (0.922)	1.00 (0.376)	0.99 (0.342)	1.00 (0.552)	1.03 (0.866)	1.09 (0.991)	1.15 (0.999)	1.21 (1.000)	1.26 (1.000)
Aluminum	1.02 (0.854)	1.02 (0.859)	1.01 (0.577)	0.99 (0.360)	0.99 (0.388)	0.99 (0.457)	1.00 (0.511)	1.01 (0.532)	1.01 (0.532)
Copper	0.99 (0.100)	1.00 (0.387)	0.99 (0.132)	0.97 (0.018)	0.97 (0.008)	0.97 (0.012)	0.96 (0.006)	0.96 (0.013)	0.96 (0.027)
Lead	0.98 (0.147)	0.99 (0.273)	0.97 (0.075)	0.92 (0.011)	0.92 (0.009)	0.94 (0.053)	0.96 (0.172)	0.98 (0.295)	0.97 (0.269)
Zinc	0.99 (0.281)	0.96 (0.084)	0.95 (0.051)	0.90 (0.002)	0.90 (0.003)	0.91 (0.005)	**0.91 (0.006)**	0.92 (0.016)	**0.92 (0.052)**
Nickel	1.01 (0.851)	1.01 (0.808)	1.00 (0.375)	0.99 (0.101)	0.98 (0.082)	0.96 (0.020)	0.94 (0.008)	0.93 (0.004)	0.92 (0.003)
Tin	1.02 (0.855)	1.05 (0.833)	1.05 (0.772)	1.03 (0.668)	1.01 (0.547)	0.97 (0.253)	0.97 (0.169)	1.00 (0.485)	1.01 (0.661)
Corn	1.01 (0.513)	0.77 (0.046)	0.70 (0.024)	0.74 (0.050)	0.77 (0.068)	0.74 (0.043)	0.71 (0.032)	0.69 (0.020)	0.64 (0.005)
Soybeans	**0.84 (0.127)**	**0.76 (0.025)**	0.74 (0.016)	0.80 (0.038)	0.87 (0.169)	0.83 (0.153)	0.78 (0.083)	0.76 (0.043)	0.71 (0.005)
Wheat	1.09 (0.862)	1.07 (0.783)	1.04 (0.601)	0.99 (0.469)	0.99 (0.461)	0.99 (0.482)	1.00 (0.483)	0.99 (0.446)	0.96 (0.338)
					Success Ratio				
Crude Oil	**0.56 (0.066)**	**0.56 (0.203)**	**0.59 (0.104)**	0.62 (0.037)	**0.70 (0.002)**	**0.70 (0.001)**	**0.73 (0.000)**	**0.71 (0.000)**	**0.76 (0.000)**
Natural Gas	**0.53 (0.265)**	**0.55 (0.184)**	0.59 (0.003)	0.60 (0.036)	**0.66 (0.007)**	0.62 (0.013)	0.62 (0.009)	0.60 (0.020)	0.60 (0.031)
Heating Oil	0.49 (0.770)	**0.58 (0.050)**	**0.62 (0.002)**	0.64 (0.006)	0.66 (0.001)	0.66 (0.001)	0.70 (0.000)	0.68 (0.000)	0.67 (0.003)
Gasoline	0.60 (0.005)	0.60 (0.013)	**0.74 (0.000)**	0.64 (0.001)	**0.70 (0.000)**	**0.67 (0.000)**	**0.66 (0.002)**	**0.71 (0.000)**	**0.76 (0.000)**
Ethanol	0.53 (0.236)	**0.63 (0.001)**	0.66 (0.000)	**0.65 (0.000)**	0.61 (0.028)	0.66 (0.001)	**0.68 (0.000)**	0.67 (0.000)	0.71 (0.000)
Gold	0.49 (0.525)	**0.58 (0.028)**	**0.60 (0.209)**	**0.57 (0.118)**	**0.55 (0.092)**	**0.61 (0.001)**	**0.64 (0.000)**	**0.61 (0.000)**	**0.62 (1.000)**
Silver	**0.51 (0.395)**	0.47 (0.763)	0.48 (0.371)	0.43 (0.570)	0.42 (0.866)	0.46 (1.000)	0.48 (1.000)	0.52 (0.000)	0.56 (0.000)
Platinum	0.49 (0.636)	0.52 (0.109)	0.48 (0.518)	0.44 (0.552)	0.36 (0.989)	0.35 (1.000)	0.32 (1.000)	0.33 (1.000)	0.28 (1.000)
Aluminum	0.48 (0.446)	0.49 (0.693)	0.50 (0.268)	**0.53 (0.080)**	**0.53 (0.019)**	**0.51 (0.003)**	0.50 (0.100)	0.45 (1.000)	0.41 (1.000)
Copper	**0.58 (0.001)**	**0.55 (0.093)**	0.55 (0.118)	0.56 (0.076)	0.57 (0.062)	0.56 (0.116)	0.57 (0.115)	**0.60 (0.065)**	0.56 (0.193)
Lead	**0.57 (0.026)**	0.55 (0.105)	0.60 (0.000)	**0.63 (0.000)**	**0.60 (0.000)**	0.54 (0.001)	0.54 (0.000)	0.55 (0.000)	0.56 (0.000)
Zinc	0.49 (0.443)	**0.60 (0.025)**	**0.66 (0.001)**	**0.72 (0.000)**	**0.68 (0.001)**	0.61 (0.050)	**0.63 (0.054)**	**0.60 (0.094)**	0.55 (0.269)
Nickel	0.49 (0.874)	**0.51 (0.739)**	**0.55 (0.202)**	**0.55 (0.170)**	**0.58 (0.146)**	**0.64 (0.003)**	**0.70 (0.000)**	**0.65 (0.000)**	**0.63 (0.000)**
Tin	0.48 (0.591)	0.44 (0.853)	0.46 (0.727)	0.49 (0.576)	0.52 (0.342)	0.50 (0.517)	0.50 (0.534)	0.54 (0.209)	**0.59 (0.021)**
Corn	**0.58 (0.025)**	0.62 (0.002)	0.62 (0.009)	0.57 (0.137)	**0.52 (0.523)**	**0.57 (0.144)**	**0.63 (0.019)**	**0.63 (0.022)**	**0.62 (0.018)**
Soybeans	**0.60 (0.003)**	**0.58 (0.059)**	**0.68 (0.000)**	**0.68 (0.000)**	**0.66 (0.004)**	**0.59 (0.081)**	**0.66 (0.005)**	**0.66 (0.007)**	**0.71 (0.001)**
Wheat	0.53 (0.248)	**0.57 (0.088)**	0.53 (0.539)	**0.51 (0.968)**	**0.58 (0.446)**	**0.53 (0.828)**	**0.57 (0.683)**	**0.57 (0.491)**	**0.58 (0.290)**

Note: Futures-Based Forecasts of nominal monthly prices by EoM Futures Curve, January 2010–2023. Bold values represent improvements over the baseline results in Table 4. The values in the brackets are the p-values for the null hypothesis of equal MSFE ratios based on the DM-test (Diebold and Mariano, 1995) and the null of no accuracy of changing direction relative to the end-of-month no-change forecast based on Pesaran and Timmermann (2009).

5.5 Longer Horizon Forecasts

We now analyze the predictive content of futures prices at long-run horizons of two to ten years, Table 8. Accurate prediction of long-term futures prices is critical for informed decision-making for long-term investments (Zhou et al., 2019). Real commodity prices should be expected to exhibit mean reversion, and existing studies have shown that futures markets adequately reflect the degree of reversion (Schwartz, 1997; Schwartz and Smith, 2000; Pindyck, 2001).

The findings indicate that, compared to the no-change benchmark, futures markets exhibit improved long-run forecasting performance for most commodities. For example, at the 5- and 10-year horizons, the MSFE ratio approaches 0.5 for most commodities, including crude oil, copper, and nickel, and falls below 0.5 for others, such as corn and soybeans. Additionally, the success ratio SR reaches 0.7 at the 5-year horizon for most commodities and approaches 0.9 at the 10-year horizon, indicating that futures-based forecasts provide exceptional directional accuracy improvements.

However, there are exceptions. futures prices do not outperform the no-change benchmark after the 2-year horizon for natural gas and wheat, and after the 5-year horizon for zinc. These exceptions are related to recent geopolitical events, as detailed in the next section. Overall, the findings demonstrate that futures markets are an effective tool for long-term real forecasts for most situations.

5.6 Robustness Over Time

We now assess the robustness of the forecast performance over time and to alternative sample start dates. Prior results have suggested that futures-based forecast performance may exhibit some forms of time variation. Specifically, Hamilton and Wu (2014) suggest that the oil futures risk premium has become both smaller but more volatile since 2005. In addition, Ellwanger and Snudden (2023b) notes improvements in forecasting performance starting from 2007 for crude oil that coincided with increases in the volume of futures contracts traded, especially at longer maturities.

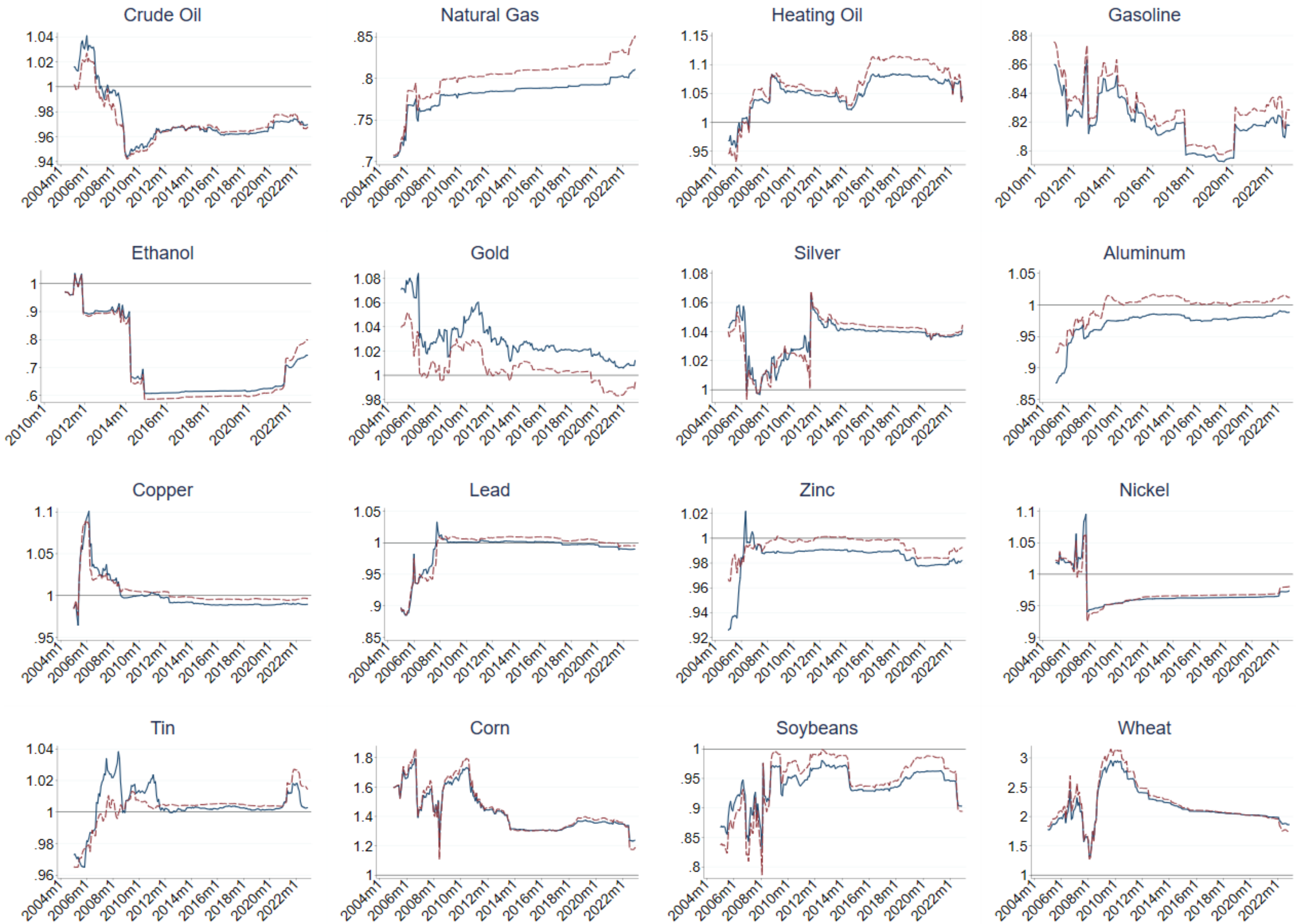
We consider an earlier starting point of the forecast evaluation sample, January 2000 instead of 2010, and report two methods to assess the temporal stability of our baseline futures-based forecasts. First, we graph the evolution of the one-month-ahead MSFE ratios over time, see Figure 2. The evolution of the evaluation criteria for one- and two-year horizons are provided in appendix B.3. In addition, the table of the end-of-period ratios and corresponding testing for the alternative forecast evaluation periods is provided in appendix Table A.4. Both exhibits document two main findings.

Table 8. Long-Run Futures-based Forecasts of Monthly Real Prices, Non-Parametric

	2	3	4	5	6	7	8	9	10
Commodity					MSFE Ratio				
Crude Oil	0.61 (0.003)	0.53 (0.003)	0.54 (0.005)	0.51 (0.000)	0.41 (0.000)	0.28 (0.000)	0.30 (0.000)	0.41 (0.000)	0.51 (0.000)
Natural Gas	0.97 (0.419)	1.21 (0.949)	1.63 (0.999)	1.57 (0.999)	1.31 (0.958)	1.46 (0.991)	2.16 (1.000)	1.75 (0.997)	1.37 (0.896)
Heating Oil	0.74 (0.000)	0.66 (0.002)	0.72 (0.004)	0.77 (0.002)	0.71 (0.000)	0.64 (0.000)	0.70 (0.005)	0.84 (0.020)	1.00 (0.517)
Gasoline	0.69 (0.002)	0.48 (0.004)	0.47 (0.006)	0.50 (0.001)	0.47 (0.000)	0.40 (0.000)	0.35 (0.000)	0.44 (0.000)	0.57 (0.001)
Ethanol	0.59 (0.027)	0.49 (0.001)	0.37 (0.000)	0.36 (0.001)	0.36 (0.000)	0.42 (0.003)	0.54 (0.014)	0.43 (0.008)	0.48 (0.007)
Gold	0.93 (0.118)	0.90 (0.133)	0.90 (0.228)	0.95 (0.384)	0.99 (0.481)	1.02 (0.525)	1.13 (0.641)	1.86 (0.932)	1.13 (0.633)
Silver	0.87 (0.016)	0.75 (0.005)	0.69 (0.004)	0.70 (0.002)	0.71 (0.002)	0.70 (0.003)	0.67 (0.002)	0.63 (0.000)	0.60 (0.000)
Platinum	0.85 (0.000)	0.88 (0.000)	0.90 (0.000)	0.91 (0.000)	0.91 (0.000)	0.92 (0.000)	0.92 (0.000)	0.92 (0.000)	0.92 (0.000)
Aluminum	0.96 (0.172)	0.98 (0.381)	1.07 (0.790)	0.93 (0.197)	0.88 (0.083)	0.94 (0.311)	0.70 (0.024)	0.57 (0.007)	0.52 (0.004)
Copper	0.88 (0.057)	0.76 (0.044)	0.61 (0.029)	0.53 (0.024)	0.52 (0.025)	0.61 (0.088)	0.45 (0.069)	0.46 (0.111)	1.79 (0.915)
Lead	0.81 (0.010)	0.64 (0.005)	0.44 (0.006)	0.38 (0.012)	0.43 (0.003)	0.48 (0.013)	0.33 (0.005)	0.27 (0.001)	0.21 (0.000)
Zinc	0.93 (0.233)	1.14 (0.751)	1.62 (0.999)	1.50 (0.978)	1.50 (1.000)	2.04 (1.000)	1.69 (1.000)	1.24 (0.966)	1.45 (0.977)
Nickel	0.80 (0.007)	0.69 (0.006)	0.65 (0.005)	0.56 (0.007)	0.54 (0.006)	0.48 (0.008)	0.40 (0.013)	0.38 (0.005)	0.32 (0.005)
Tin	0.99 (0.442)	0.99 (0.451)	0.98 (0.380)	0.96 (0.246)	0.96 (0.198)	0.94 (0.123)	0.93 (0.143)	0.94 (0.152)	0.94 (0.203)
Corn	0.57 (0.012)	0.42 (0.000)	0.34 (0.001)	0.35 (0.000)	0.36 (0.000)	0.34 (0.000)	0.33 (0.001)	0.33 (0.002)	0.29 (0.003)
Soybeans	0.67 (0.032)	0.51 (0.007)	0.42 (0.001)	0.34 (0.001)	0.36 (0.003)	0.40 (0.009)	0.44 (0.024)	0.44 (0.006)	0.35 (0.021)
Wheat	0.89 (0.166)	0.85 (0.091)	0.91 (0.228)	0.98 (0.427)	1.10 (0.768)	1.22 (0.912)	1.32 (0.933)	1.54 (0.979)	1.38 (0.881)
					Success Ratio				
Crude Oil	0.75 (0.000)	0.77 (0.000)	0.63 (0.107)	0.75 (0.011)	0.88 (0.000)	0.90 (0.000)	0.95 (0.117)	0.96 (1.000)	0.92 (0.850)
Natural Gas	0.62 (0.021)	0.53 (0.255)	0.36 (0.886)	0.31 (0.958)	0.39 (1.000)	0.40 (1.000)	0.18 (1.000)	0.35 (1.000)	0.46 (1.000)
Heating Oil	0.81 (0.000)	0.81 (0.000)	0.72 (0.005)	0.70 (0.010)	0.77 (0.002)	0.82 (0.006)	0.69 (0.516)	0.65 (0.946)	0.60 (0.953)
Gasoline	0.70 (0.000)	0.73 (0.000)	0.73 (0.000)	0.69 (0.269)	0.78 (0.057)	0.82 (0.027)	0.85 (0.266)	0.86 (0.867)	0.81 (0.871)
Ethanol	0.73 (0.000)	0.78 (0.000)	0.77 (0.000)	0.72 (0.995)	0.67 (0.996)	0.73 (0.984)	0.82 (0.975)	0.84 (0.974)	0.81 (0.945)
Gold	0.50 (1.000)	0.46 (1.000)	0.51 (1.000)	0.54 (1.000)	0.49 (1.000)	0.55 (1.000)	0.54 (1.000)	0.71 (1.000)	0.51 (1.000)
Silver	0.63 (0.009)	0.77 (0.000)	0.73 (0.000)	0.70 (1.000)	0.71 (1.000)	0.63 (1.000)	0.85 (1.000)	1.00 (1.000)	0.97 (1.000)
Platinum	0.84 (0.000)	0.88 (0.000)	0.81 (0.590)	0.90 (0.920)	0.99 (1.000)	1.00 (1.000)	1.00 (1.000)	1.00 (1.000)	1.00 (1.000)
Aluminum	0.56 (0.064)	0.55 (0.165)	0.49 (0.522)	0.57 (0.151)	0.48 (1.000)	0.52 (0.362)	0.74 (0.005)	0.84 (0.000)	0.78 (0.004)
Copper	0.59 (1.000)	0.55 (1.000)	0.62 (1.000)	0.74 (1.000)	0.69 (1.000)	0.67 (1.000)	0.72 (1.000)	0.78 (1.000)	0.89 (1.000)
Lead	0.67 (0.061)	0.61 (1.000)	0.74 (1.000)	0.71 (1.000)	0.72 (1.000)	0.86 (1.000)	0.93 (1.000)	0.94 (1.000)	1.00 (1.000)
Zinc	0.58 (0.120)	0.46 (0.621)	0.50 (1.000)	0.37 (1.000)	0.26 (1.000)	0.12 (1.000)	0.23 (1.000)	0.29 (1.000)	0.41 (1.000)
Nickel	0.55 (0.000)	0.54 (0.000)	0.62 (0.000)	0.66 (1.000)	0.66 (1.000)	0.73 (1.000)	0.71 (1.000)	0.69 (1.000)	0.73 (1.000)
Tin	0.54 (1.000)	0.60 (1.000)	0.63 (1.000)	0.70 (1.000)	0.75 (1.000)	0.63 (1.000)	0.62 (1.000)	0.63 (1.000)	0.62 (1.000)
Corn	0.59 (0.024)	0.69 (0.000)	0.72 (0.000)	0.74 (0.000)	0.81 (0.000)	0.77 (0.005)	0.77 (0.029)	0.82 (0.043)	0.73 (0.854)
Soybeans	0.62 (0.004)	0.78 (0.000)	0.73 (0.000)	0.69 (0.999)	0.68 (0.000)	0.75 (0.000)	0.92 (0.000)	0.98 (1.000)	1.00 (1.000)
Wheat	0.55 (0.371)	0.55 (0.000)	0.53 (0.000)	0.52 (1.000)	0.47 (1.000)	0.41 (1.000)	0.36 (1.000)	0.25 (1.000)	0.43 (1.000)

Notes: Futures-based forecasts of monthly average spot prices by the end-of-month (EOM) futures prices, January 2010–2023. The numbers 2 through 10 in the top row represent the forecast horizon in years. The bold values represent improvements over the random walk, no-change forecast. The values in the brackets are the p-values for the null hypothesis of equal MSFE ratios based on the DM-test (Diebold and Mariano, 1995) and random directional accuracy following Pesaran and Timmermann (2009).

Figure 2. Evolution of MSFEs Criteria For Futures-Based Forecasts, One-Month Ahead.



Note: The blue line represents forecasts of real prices using End-of-Month (EoM) futures, while the red line illustrates forecasts of nominal prices using EoM. A horizontal reference line is drawn at the value of 1 to serve as a benchmark for evaluating MSFE values, which are reported relative to the average price of a no-change forecast.

First, starting around 2010, futures-based forecasts generally begin to consistently outperform random walk predictions for the majority of commodities studied. These improvement in forecast accuracy correlate with increased trading volumes (see appendix Figure A3), suggesting a link between market depth and predictive performance. Notability, these gains in forecast precision have been quite stable over the last two decades. This is indicative of the robust performance of futures-based forecasts post-financialization.

However, the last two years exhibits a marked decrease in forecasting accuracy for natural gas. This decline is particularly pronounced at up to one-year horizons and explains the poor forecast performance observed in the baseline sample. In fact, before this recent episode, natural gas had exhibited some of the best forecast performance across commodity markets.

6 Conclusion

We conclude with three practical recommendations for constructing futures-based forecasts. First, we find empirical support for the use of the latest market expectations contained within end-of-month futures prices, as they generally outperform the accuracy of forecasts built on averaged futures prices. This is also practically convenient in constructing real-time forecasts, with futures prices being publicly available and continuously updated. Second, our analysis does not suggest general gains from adopting parametric approaches, and thus we recommend forecasts to utilize simple non-parametric approaches. Third, we recommend forecasters careful consider the expectations embedded in futures contracts with the specific forecast horizons of interest. By adhering to these simple guidelines, we believe forecasters can utilize futures prices for real-time forecasts of period average prices of commodities.

Our results suggest that the average price of many primary commodities is predictable in real-time, especially at the six-month horizon and beyond. Notably, energy commodities, transition metals, and certain agricultural products show the most substantial forecast accuracy improvements. This contributes to the broader understanding of futures markets' predictive capabilities and underscores the heterogeneity across different commodity sectors. This predictability offers valuable insights for market participants and policymakers, particularly in informed decision-making regarding resource allocation, investment, and policy formulation.

Ultimately, the potential gains from ongoing refinement of futures-based forecasts underscore the importance of further research. This study highlights the current capabilities and limitations of using futures markets for price forecasting. Further enhancements in precision, robustness, and applicability of these forecasts to under-explored commodities are warranted.

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Online Appendix

A Data Appendix

Consumer price index: The real-time monthly seasonally adjusted U.S. consumer price index for all urban consumers is obtained from Economic Indicators published by the Council of Economic Advisers and obtained from the macroeconomic real-time database of the Federal Reserve Bank of Philadelphia. The CPI vintages are subject to revision and are typically subject to a one-month publication delay. Missing observations of CPI are nowcasted using that vintages average historical growth rate from 1973M1.

Spot price data: Daily closing prices for all spot prices are used to calculate both the monthly average and end-of-month prices. The end-of-month price is the closing price on the last trading day of the month. Following standard practices, monthly average prices are the simple average of daily closing prices. Spot prices are not subject to revisions and are observed in real time. All spot prices are obtained from Bloomberg except crude oil and heating oil, which are obtained from the EIA.

Table A.1. Bloomberg Tickers / Sources for Commodity Spot Prices and Sample Periods

Commodity	Market	Ticker	Source	Sample Start
Energy				
Crude oil	Cushing, OK		EIA	1986.01
Natural Gas	Henry Hub	NGUSHHUB	Bloomberg	1999.01
Heating Oil	New York		EIA	1986.06
Gasoline	New York	RBOB87PM	Bloomberg	2003.11
Ethanol	Chicago	ETHNCHIC	Bloomberg	2007.02
Precious Metals				
Gold		XAUUSD	Bloomberg	1975.01
Silver		XAGUSD	Bloomberg	1973.01
Platinum		XPTUSD	Bloomberg	1987.01
Base Metals				
Aluminum	LME	LMAHDY	Bloomberg	1987.08
Copper	LME	LMCADY	Bloomberg	1986.04
Lead	LME	LMPBDY	Bloomberg	1987.01
Nickel	LME	LMNIDY	Bloomberg	1987.01
Tin	LME	LMSNDY	Bloomberg	1989.06
Zinc	LME	LMZSDY	Bloomberg	1989.01
Agricultural				
Corn	Chicago	CORNCH2Y	Bloomberg	1996.01
Soybeans	Chicago	SOYBCH1Y	Bloomberg	1996.01
Wheat	Chicago	WEATCHEL	Bloomberg	1992.01

B Additional Results

B.1 Comparison of No-Change Benchmarks

We empirically validate the appropriateness of the end-of-month versus average price no-change for monthly average real prices for all primary commodities. We employ two forecast evaluation criteria: the Mean Squared Forecast Error (MSFE) ratio and a measure of directional accuracy, termed success ratios. The MSFE ratio for the h-step-ahead forecast, $MSFE_h^{ratio}$, is computed as the quotient of the MSFE of the model-based forecast and the MSFE of the no-change benchmark:

$$MSFE_k^{ratio} = \frac{E[\sum_{q=1}^{Q}(\bar{R}_{q+h} - R_{q,n|q})^2]}{E[\sum_{q=1}^{Q}(\bar{R}_{q+h} - \bar{R}_{q|q})^2]}, \tag{A1}$$

where $\bar{R}_{q|q}$ and $R_{q,n|q}$ represent the monthly average and end-of-month no-change forecast for the h step ahead average price $\bar{R}_{q+h}$, for all periods of the evaluation sample, denoted as $q = 1, 2, \ldots, Q$. The null hypothesis, suggesting an equal MSFE of the model-based forecast relative to the no-change forecast, is tested following the methodology of Diebold and Mariano (1995) and compared against standard normal critical values.

Directional accuracy is evaluated using the mean directional accuracy. This metric describes the fraction of times the forecasting model is able to correctly predict the change in the direction of the real price of a commodity. The calculation is as follows:

$$SR_k = \frac{1}{Q}\sum_{q=1}^{Q} \mathbb{1}\{sgn(\bar{R}_{q+h} - \bar{R}_q) = sgn(R_{q,n|q} - \bar{R}_{q|q})\}, \tag{A2}$$

where sgn is a sign function and $\mathbb{1}$ is an indicator function. The test statistic is calculated following Pesaran and Timmermann (2009). The null hypothesis is that the futures-based forecast should be no more successful at predicting the direction of change in the price of the respective commodity, with a success probability of 0.5. Therefore, a success ratio above 0.5 can be interpreted as an improvement over the no-change forecast.

The no-change forecasts are implemented in real-time; see section 4. Across all commodities, the MSFE ratios remain under unity at short-run horizons, and the success ratios exceed 0.5, see Table A.2. Both the magnitude and convergence of forecast criteria closely reflect values for series closely approximated by a random walk. Consistent with the findings for crude oil (Ellwanger and Snudden, 2023a), the forecast gains are significant for both criteria for the majority of commodities

Table A.2. Real-Time End-of-Month versus Monthly Average No-Change Forecast

	1	3	6	9	12	15	18	21	24
Commodity					MSFE Ratio				
Crude Oil	0.54 (0.000)	0.91 (0.008)	0.97 (0.303)	0.96 (0.058)	0.97 (0.010)	0.97 (0.194)	0.98 (0.205)	0.99 (0.084)	1.00 (0.249)
Natural Gas	0.52 (0.000)	0.88 (0.000)	0.93 (0.044)	0.96 (0.072)	0.92 (0.075)	1.01 (0.276)	1.00 (0.085)	0.97 (0.369)	0.95 (0.534)
Heating Oil	0.60 (0.000)	0.90 (0.009)	0.95 (0.038)	0.96 (0.259)	0.99 (0.155)	0.98 (0.137)	0.99 (0.060)	0.99 (0.223)	1.00 (0.149)
Gasoline	0.60 (0.000)	0.93 (0.002)	1.02 (0.165)	1.03 (0.117)	1.00 (0.152)	0.99 (0.088)	1.00 (0.259)	1.01 (0.294)	1.02 (0.216)
Ethanol	0.91 (0.000)	1.31 (0.225)	1.20 (0.017)	1.13 (0.910)	1.13 (0.101)	1.12 (0.723)	1.13 (0.469)	1.14 (0.213)	1.13 (0.511)
Gold	0.70 (0.000)	0.94 (0.011)	0.94 (0.004)	0.99 (0.112)	0.98 (0.017)	0.99 (0.190)	0.98 (0.317)	0.98 (0.423)	0.99 (0.559)
Silver	0.82 (0.000)	0.95 (0.070)	0.98 (0.060)	1.00 (0.175)	1.01 (0.041)	1.03 (0.362)	1.01 (0.419)	1.00 (0.277)	1.01 (0.345)
Platinum	0.59 (0.000)	0.93 (0.003)	0.98 (0.004)	0.98 (0.190)	0.99 (0.001)	1.01 (0.306)	0.97 (0.038)	0.97 (0.009)	0.97 (0.005)
Aluminum	0.59 (0.000)	0.94 (0.107)	0.97 (0.077)	1.00 (0.435)	1.00 (0.196)	1.04 (0.799)	1.03 (0.854)	1.02 (0.548)	1.03 (0.510)
Copper	0.64 (0.000)	0.91 (0.010)	0.96 (0.163)	0.98 (0.011)	0.99 (0.054)	1.02 (0.129)	1.02 (0.135)	1.01 (0.086)	1.02 (0.305)
Lead	0.70 (0.000)	0.99 (0.001)	0.97 (0.353)	1.00 (0.049)	1.03 (0.329)	1.05 (0.630)	1.05 (0.399)	1.02 (0.549)	1.03 (0.853)
Zinc	0.56 (0.000)	0.91 (0.000)	0.98 (0.258)	1.03 (0.592)	1.02 (0.596)	1.02 (0.782)	1.01 (0.775)	1.00 (0.760)	1.01 (0.897)
Nickel	0.67 (0.000)	0.92 (0.000)	0.98 (0.037)	0.99 (0.300)	0.98 (0.340)	1.02 (0.436)	1.01 (0.151)	1.02 (0.290)	1.02 (0.308)
Tin	0.55 (0.000)	0.86 (0.000)	0.97 (0.027)	1.00 (0.056)	0.99 (0.049)	1.02 (0.259)	1.03 (0.351)	1.03 (0.678)	1.03 (0.667)
Corn	0.67 (0.000)	0.92 (0.002)	0.97 (0.537)	0.99 (0.185)	0.98 (0.108)	1.00 (0.020)	1.00 (0.014)	1.00 (0.050)	1.00 (0.203)
Soybeans	0.59 (0.000)	0.96 (0.000)	1.02 (0.525)	1.04 (0.090)	1.03 (0.217)	1.02 (0.029)	1.01 (0.400)	1.01 (0.270)	1.01 (0.155)
Wheat	0.54 (0.000)	0.90 (0.014)	0.93 (0.205)	0.96 (0.201)	1.02 (0.266)	1.04 (0.298)	1.02 (0.208)	0.99 (0.514)	1.01 (0.772)
					Success Ratio				
Crude Oil	0.74 (0.000)	0.59 (0.008)	0.53 (0.303)	0.57 (0.058)	0.59 (0.010)	0.54 (0.194)	0.54 (0.205)	0.56 (0.084)	0.53 (0.249)
Natural Gas	0.76 (0.000)	0.66 (0.000)	0.56 (0.044)	0.57 (0.072)	0.57 (0.075)	0.53 (0.276)	0.56 (0.085)	0.52 (0.369)	0.50 (0.534)
Heating Oil	0.73 (0.000)	0.58 (0.009)	0.57 (0.038)	0.53 (0.259)	0.54 (0.155)	0.54 (0.137)	0.55 (0.060)	0.52 (0.223)	0.53 (0.149)
Gasoline	0.69 (0.000)	0.60 (0.002)	0.56 (0.165)	0.56 (0.117)	0.55 (0.152)	0.55 (0.088)	0.53 (0.259)	0.52 (0.294)	0.53 (0.216)
Ethanol	0.76 (0.000)	0.53 (0.225)	0.56 (0.017)	0.45 (0.910)	0.54 (0.101)	0.47 (0.723)	0.50 (0.469)	0.52 (0.213)	0.49 (0.511)
Gold	0.73 (0.000)	0.58 (0.011)	0.60 (0.004)	0.55 (0.112)	0.58 (0.017)	0.54 (0.190)	0.52 (0.317)	0.51 (0.423)	0.49 (0.559)
Silver	0.73 (0.000)	0.56 (0.070)	0.58 (0.060)	0.56 (0.175)	0.59 (0.041)	0.54 (0.362)	0.52 (0.419)	0.54 (0.277)	0.53 (0.345)
Platinum	0.75 (0.000)	0.60 (0.003)	0.61 (0.004)	0.54 (0.190)	0.61 (0.001)	0.53 (0.306)	0.58 (0.038)	0.58 (0.009)	0.59 (0.005)
Aluminum	0.70 (0.000)	0.54 (0.107)	0.54 (0.077)	0.50 (0.435)	0.52 (0.196)	0.47 (0.799)	0.45 (0.854)	0.49 (0.548)	0.49 (0.510)
Copper	0.65 (0.000)	0.58 (0.010)	0.53 (0.163)	0.57 (0.011)	0.55 (0.054)	0.53 (0.129)	0.53 (0.135)	0.54 (0.086)	0.51 (0.305)
Lead	0.69 (0.000)	0.60 (0.001)	0.51 (0.353)	0.55 (0.049)	0.51 (0.329)	0.48 (0.630)	0.50 (0.399)	0.49 (0.549)	0.46 (0.853)
Zinc	0.72 (0.000)	0.63 (0.000)	0.52 (0.258)	0.49 (0.592)	0.49 (0.596)	0.46 (0.782)	0.46 (0.775)	0.46 (0.760)	0.44 (0.897)
Nickel	0.72 (0.000)	0.66 (0.000)	0.57 (0.037)	0.52 (0.300)	0.52 (0.340)	0.51 (0.436)	0.54 (0.151)	0.52 (0.290)	0.52 (0.308)
Tin	0.72 (0.000)	0.64 (0.000)	0.58 (0.027)	0.56 (0.056)	0.56 (0.049)	0.52 (0.259)	0.51 (0.351)	0.48 (0.678)	0.48 (0.667)
Corn	0.73 (0.000)	0.60 (0.002)	0.50 (0.537)	0.53 (0.185)	0.55 (0.108)	0.58 (0.020)	0.58 (0.014)	0.57 (0.050)	0.54 (0.203)
Soybeans	0.70 (0.000)	0.62 (0.000)	0.50 (0.525)	0.54 (0.090)	0.53 (0.217)	0.58 (0.029)	0.51 (0.400)	0.52 (0.270)	0.54 (0.155)
Wheat	0.65 (0.000)	0.57 (0.014)	0.53 (0.205)	0.53 (0.201)	0.52 (0.266)	0.52 (0.298)	0.53 (0.208)	0.50 (0.514)	0.47 (0.772)

Notes: Real-time end-of-month versus monthly average no-change forecasts for the real price level, 2000-2023. Forecasts for ethanol and gasoline start in 2006 due to data constraints. The forecast criteria include the MSFE ratio expressed relative to the monthly average no-change forecast. Success ratios represent the fraction of times the forecast correctly predicts the direction of the change in the real price level.

up to one year ahead.

These empirical findings reinforce the necessity to test relative to the end-of-period no-change forecast when evaluating period average forecasts of primary commodities. All forecasts in the paper are thus reported and tested against the end-of-month no-change forecast.

B.2 Five Day End-of-Month Futures Average

Table A.3. Futures-based Forecasts of Monthly Average Real Prices, Non-Parametric, Constructed using Five Day End-of-Month Futures Average

	1	3	6	9	12	15	18	21	24
Commodity					MSFE Ratio				
Crude Oil	1.20 (0.977)	0.95 (0.057)	0.88 (0.027)	0.87 (0.089)	0.83 (0.070)	0.77 (0.026)	0.71 (0.013)	0.66 (0.007)	0.61 (0.003)
Natural Gas	1.19 (0.980)	1.03 (0.657)	0.98 (0.427)	1.07 (0.667)	1.07 (0.669)	**0.96 (0.354)**	**0.96 (0.387)**	**0.96 (0.378)**	0.97 (0.400)
Heating Oil	1.47 (0.997)	1.00 (0.481)	0.97 (0.276)	0.93 (0.059)	0.87 (0.006)	0.86 (0.002)	0.82 (0.000)	0.79 (0.000)	0.74 (0.000)
Gasoline	0.97 (0.394)	0.77 (0.005)	0.70 (0.004)	0.82 (0.048)	0.89 (0.093)	0.83 (0.028)	0.75 (0.010)	0.73 (0.009)	0.70 (0.003)
Ethanol	1.18 (0.646)	0.75 (0.123)	0.84 (0.239)	0.84 (0.181)	0.77 (0.123)	**0.70 (0.051)**	0.68 (0.046)	**0.62 (0.039)**	**0.57 (0.025)**
Gold	**0.97 (0.261)**	1.01 (0.600)	**0.99 (0.450)**	0.99 (0.413)	0.98 (0.377)	0.98 (0.336)	0.97 (0.275)	0.95 (0.185)	0.93 (0.125)
Silver	**0.99 (0.468)**	1.04 (0.857)	1.00 (0.501)	0.98 (0.312)	0.97 (0.188)	**0.95 (0.107)**	**0.92 (0.040)**	0.89 (0.022)	**0.86 (0.023)**
Platinum	1.07 (0.950)	1.02 (0.745)	0.94 (0.088)	0.91 (0.033)	**0.88 (0.013)**	**0.86 (0.003)**	**0.85 (0.000)**	**0.84 (0.000)**	**0.84 (0.000)**
Aluminum	1.10 (0.891)	1.00 (0.516)	0.98 (0.297)	0.96 (0.129)	**0.94 (0.031)**	**0.94 (0.049)**	**0.95 (0.099)**	**0.95 (0.131)**	**0.94 (0.121)**
Copper	1.00 (0.514)	**0.96 (0.166)**	0.97 (0.198)	0.94 (0.109)	0.93 (0.079)	0.92 (0.058)	**0.89 (0.040)**	0.88 (0.040)	**0.87 (0.054)**
Lead	1.11 (0.923)	0.99 (0.422)	0.96 (0.175)	0.88 (0.043)	0.87 (0.033)	0.87 (0.061)	0.86 (0.066)	0.85 (0.041)	0.82 (0.020)
Zinc	1.15 (0.961)	0.95 (0.119)	0.93 (0.114)	0.89 (0.038)	0.90 (0.068)	0.92 (0.118)	0.93 (0.172)	0.94 (0.227)	0.94 (0.279)
Nickel	1.07 (0.891)	1.01 (0.554)	**0.96 (0.147)**	**0.93 (0.104)**	**0.92 (0.112)**	**0.87 (0.036)**	**0.83 (0.026)**	**0.80 (0.012)**	**0.78 (0.009)**
Tin	1.08 (0.920)	1.02 (0.601)	1.01 (0.532)	1.00 (0.497)	0.99 (0.429)	0.95 (0.218)	**0.94 (0.181)**	0.98 (0.323)	0.99 (0.407)
Corn	**0.96 (0.365)**	0.77 (0.048)	0.69 (0.029)	0.72 (0.052)	0.74 (0.064)	0.68 (0.038)	0.64 (0.034)	0.62 (0.029)	0.58 (0.013)
Soybeans	0.90 (0.120)	**0.76 (0.013)**	0.73 (0.025)	0.78 (0.047)	0.84 (0.156)	0.78 (0.125)	0.73 (0.085)	0.73 (0.076)	0.68 (0.034)
Wheat	1.12 (0.880)	1.07 (0.734)	1.05 (0.626)	0.99 (0.473)	**0.95 (0.380)**	**0.92 (0.301)**	**0.93 (0.250)**	**0.92 (0.197)**	**0.88 (0.163)**
					Success Ratio				
Crude Oil	0.47 (0.709)	**0.57 (0.039)**	0.57 (0.060)	0.58 (0.069)	0.68 (0.000)	**0.71 (0.000)**	0.66 (0.001)	**0.65 (0.002)**	**0.76 (0.000)**
Natural Gas	**0.53 (0.249)**	**0.56 (0.064)**	0.60 (0.002)	0.61 (0.011)	**0.66 (0.002)**	0.64 (0.005)	**0.65 (0.007)**	0.63 (0.009)	0.62 (0.018)
Heating Oil	**0.53 (0.182)**	**0.57 (0.057)**	**0.66 (0.000)**	0.66 (0.002)	0.75 (0.000)	0.82 (0.000)	0.81 (0.000)	0.80 (0.000)	0.77 (0.000)
Gasoline	0.56 (0.051)	0.60 (0.019)	**0.72 (0.000)**	0.64 (0.001)	0.62 (0.001)	**0.63 (0.000)**	0.63 (0.007)	**0.71 (0.000)**	0.70 (0.000)
Ethanol	**0.58 (0.009)**	**0.60 (0.012)**	0.63 (0.000)	0.61 (0.012)	0.64 (0.018)	0.68 (0.000)	**0.65 (0.001)**	0.67 (0.000)	0.73 (0.000)
Gold	**0.56 (0.033)**	0.47 (0.882)	**0.53 (0.052)**	**0.57 (0.097)**	**0.55 (0.262)**	**0.61 (0.000)**	**0.60 (0.000)**	**0.60 (0.000)**	**0.53 (0.000)**
Silver	**0.55 (0.100)**	**0.53 (0.295)**	0.58 (0.155)	0.62 (0.140)	0.59 (0.395)	0.62 (0.132)	**0.68 (0.000)**	0.67 (0.000)	**0.64 (0.001)**
Platinum	0.47 (0.707)	0.47 (0.851)	0.60 (0.096)	0.62 (0.162)	0.68 (0.075)	0.73 (0.023)	0.74 (0.006)	0.77 (0.001)	0.77 (0.008)
Aluminum	**0.55 (0.079)**	**0.52 (0.292)**	0.49 (0.539)	0.50 (0.452)	**0.53 (0.252)**	**0.54 (0.219)**	0.53 (0.293)	**0.58 (0.062)**	0.56 (0.116)
Copper	**0.55 (0.118)**	0.53 (0.348)	0.60 (0.163)	0.59 (0.522)	**0.64 (0.145)**	0.63 (0.317)	**0.61 (0.160)**	0.59 (1.000)	0.59 (1.000)
Lead	0.51 (0.430)	0.52 (0.352)	0.52 (0.466)	0.58 (0.087)	0.57 (0.064)	0.61 (0.138)	0.63 (0.202)	0.63 (0.289)	0.65 (0.298)
Zinc	0.51 (0.581)	**0.53 (0.252)**	**0.58 (0.018)**	**0.57 (0.019)**	**0.61 (0.002)**	**0.62 (0.004)**	0.60 (0.019)	0.57 (0.034)	0.58 (0.122)
Nickel	0.50 (0.500)	0.49 (0.541)	0.48 (0.635)	**0.53 (0.159)**	**0.56 (0.009)**	**0.53 (0.130)**	**0.52 (0.152)**	**0.60 (0.014)**	**0.62 (0.000)**
Tin	0.47 (0.843)	**0.51 (0.417)**	**0.52 (0.101)**	**0.55 (0.007)**	**0.56 (0.000)**	**0.55 (0.000)**	**0.60 (0.000)**	**0.59 (0.000)**	**0.56 (0.000)**
Corn	**0.59 (0.009)**	0.62 (0.001)	**0.66 (0.001)**	**0.58 (0.050)**	0.51 (0.443)	0.51 (0.441)	**0.57 (0.117)**	**0.57 (0.063)**	0.58 (0.035)
Soybeans	**0.58 (0.015)**	**0.60 (0.012)**	**0.62 (0.011)**	**0.64 (0.007)**	**0.61 (0.023)**	**0.59 (0.110)**	**0.57 (0.083)**	**0.60 (0.041)**	**0.63 (0.002)**
Wheat	**0.61 (0.000)**	**0.64 (0.001)**	**0.59 (0.023)**	**0.52 (0.547)**	0.48 (0.870)	0.48 (0.758)	0.53 (0.437)	0.54 (0.462)	**0.56 (0.269)**

Notes: Futures-based forecasts of monthly average spot prices constructed using the five-day end-of-month average of futures prices, January 2010–2023. Bold values represent improvements over the baseline results in Table 4. The values in the brackets are the p-values for the null hypothesis of equal MSFE ratios based on the DM-test (Diebold and Mariano, 1995) and the null hypothesis of no accuracy of changing direction relative to the random walk, no-change forecast based on Pesaran and Timmermann (2009).

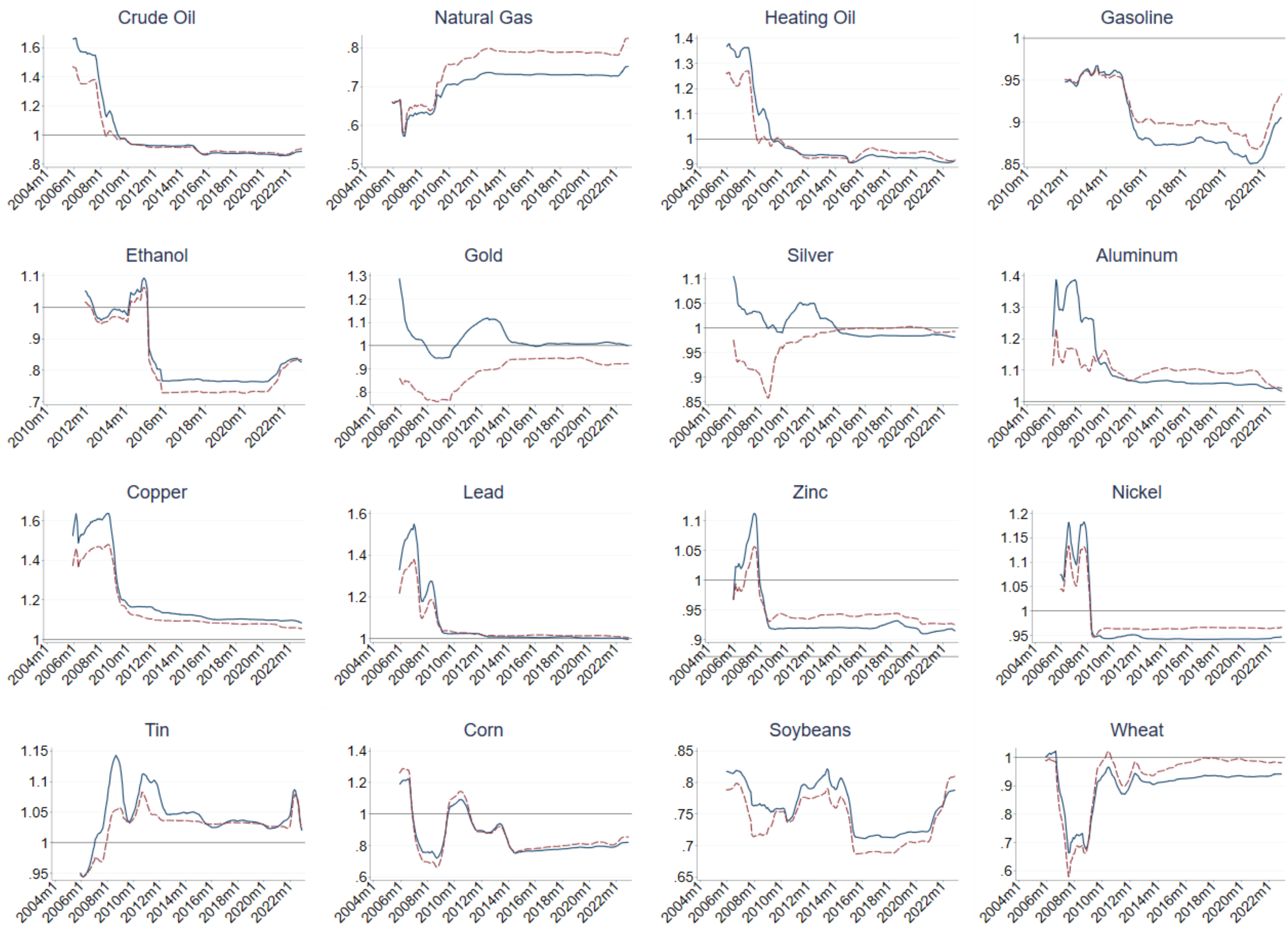
B.3 Robustness Over Time

Table A.4. Futures-based Forecasts of Monthly Average Real Prices, Non-Parametric, Sample Starting 2000

	1	3	6	9	12	15	18	21	24
Commodity					MSFE Ratio				
Crude Oil	1.20 (0.977)	0.95 (0.057)	0.88 (0.027)	0.87 (0.089)	0.83 (0.070)	0.77 (0.026)	0.71 (0.013)	0.66 (0.007)	0.61 (0.003)
Natural Gas	1.19 (0.980)	1.03 (0.657)	0.98 (0.427)	1.07 (0.667)	1.07 (0.669)	**0.96 (0.354)**	**0.96 (0.387)**	**0.96 (0.378)**	0.97 (0.400)
Heating Oil	1.47 (0.997)	1.00 (0.481)	0.97 (0.276)	0.93 (0.059)	0.87 (0.006)	0.86 (0.002)	0.82 (0.000)	0.79 (0.000)	0.74 (0.000)
Gasoline	0.97 (0.394)	0.77 (0.005)	0.70 (0.004)	0.82 (0.048)	0.89 (0.093)	0.83 (0.028)	0.75 (0.010)	0.73 (0.009)	0.70 (0.003)
Ethanol	1.18 (0.646)	0.75 (0.123)	0.84 (0.239)	0.84 (0.181)	0.77 (0.123)	**0.70 (0.051)**	0.68 (0.046)	**0.62 (0.039)**	**0.57 (0.025)**
Gold	**0.97 (0.261)**	1.01 (0.600)	**0.99 (0.450)**	0.99 (0.413)	0.98 (0.377)	0.98 (0.336)	0.97 (0.275)	0.95 (0.185)	0.93 (0.125)
Silver	**0.99 (0.468)**	1.04 (0.857)	1.00 (0.501)	0.98 (0.312)	0.97 (0.188)	**0.95 (0.107)**	**0.92 (0.040)**	0.89 (0.022)	**0.86 (0.023)**
Platinum	1.07 (0.950)	1.02 (0.745)	0.94 (0.088)	0.91 (0.033)	**0.88 (0.013)**	**0.86 (0.003)**	**0.85 (0.000)**	**0.84 (0.000)**	**0.84 (0.000)**
Aluminum	1.10 (0.891)	1.00 (0.516)	0.98 (0.297)	0.96 (0.129)	**0.94 (0.031)**	**0.94 (0.049)**	**0.95 (0.099)**	**0.95 (0.131)**	**0.94 (0.121)**
Copper	1.00 (0.514)	**0.96 (0.166)**	0.97 (0.198)	0.94 (0.109)	0.93 (0.079)	0.92 (0.058)	**0.89 (0.040)**	0.88 (0.040)	**0.87 (0.054)**
Lead	1.11 (0.923)	0.99 (0.422)	0.96 (0.175)	0.88 (0.043)	0.87 (0.033)	0.87 (0.061)	0.86 (0.066)	0.85 (0.041)	0.82 (0.020)
Zinc	1.15 (0.961)	0.95 (0.119)	0.93 (0.114)	0.89 (0.038)	0.90 (0.068)	0.92 (0.118)	0.93 (0.172)	0.94 (0.227)	0.94 (0.279)
Nickel	1.07 (0.891)	1.01 (0.554)	**0.96 (0.147)**	**0.93 (0.104)**	**0.92 (0.112)**	**0.87 (0.036)**	**0.83 (0.026)**	**0.80 (0.012)**	**0.78 (0.009)**
Tin	1.08 (0.920)	1.02 (0.601)	1.01 (0.532)	1.00 (0.497)	0.99 (0.429)	0.95 (0.218)	**0.94 (0.181)**	0.98 (0.323)	0.99 (0.407)
Corn	**0.96 (0.365)**	0.77 (0.048)	0.69 (0.029)	0.72 (0.052)	0.74 (0.064)	0.68 (0.038)	0.64 (0.034)	0.62 (0.029)	0.58 (0.013)
Soybeans	0.90 (0.120)	**0.76 (0.013)**	0.73 (0.025)	0.78 (0.047)	0.84 (0.156)	0.78 (0.125)	0.73 (0.085)	0.73 (0.076)	0.68 (0.034)
Wheat	1.12 (0.880)	1.07 (0.734)	1.05 (0.626)	0.99 (0.473)	**0.95 (0.380)**	**0.92 (0.301)**	**0.93 (0.250)**	**0.92 (0.197)**	**0.88 (0.163)**
					Success Ratio				
Crude Oil	0.47 (0.709)	**0.57 (0.039)**	0.57 (0.060)	0.58 (0.069)	0.68 (0.000)	**0.71 (0.000)**	0.66 (0.001)	**0.65 (0.002)**	**0.76 (0.000)**
Natural Gas	**0.53 (0.249)**	**0.56 (0.064)**	0.60 (0.002)	0.61 (0.011)	**0.66 (0.002)**	0.64 (0.005)	**0.65 (0.007)**	0.63 (0.009)	0.62 (0.018)
Heating Oil	**0.53 (0.182)**	**0.57 (0.057)**	**0.66 (0.000)**	0.66 (0.002)	0.75 (0.000)	0.82 (0.000)	0.81 (0.000)	0.80 (0.000)	0.77 (0.000)
Gasoline	0.56 (0.051)	0.60 (0.019)	**0.72 (0.000)**	0.64 (0.001)	0.62 (0.001)	**0.63 (0.000)**	0.63 (0.007)	**0.71 (0.000)**	0.70 (0.000)
Ethanol	**0.58 (0.009)**	**0.60 (0.012)**	0.63 (0.000)	0.61 (0.012)	0.64 (0.018)	0.68 (0.000)	**0.65 (0.001)**	0.67 (0.000)	0.73 (0.000)
Gold	**0.56 (0.033)**	0.47 (0.882)	**0.53 (0.052)**	**0.57 (0.097)**	**0.55 (0.262)**	**0.61 (0.000)**	**0.60 (0.000)**	**0.60 (0.000)**	**0.53 (0.000)**
Silver	**0.55 (0.100)**	**0.53 (0.295)**	0.58 (0.155)	0.62 (0.140)	0.59 (0.395)	0.62 (0.132)	**0.68 (0.000)**	0.67 (0.000)	**0.64 (0.001)**
Platinum	0.47 (0.707)	0.47 (0.851)	0.60 (0.096)	0.62 (0.162)	0.68 (0.075)	0.73 (0.023)	0.74 (0.006)	0.77 (0.001)	0.77 (0.008)
Aluminum	**0.55 (0.079)**	**0.52 (0.292)**	0.49 (0.539)	0.50 (0.452)	**0.53 (0.252)**	**0.54 (0.219)**	0.53 (0.293)	**0.58 (0.062)**	0.56 (0.116)
Copper	**0.55 (0.118)**	0.53 (0.348)	0.60 (0.163)	0.59 (0.522)	**0.64 (0.145)**	0.63 (0.317)	**0.61 (0.160)**	0.59 (1.000)	0.59 (1.000)
Lead	0.51 (0.430)	0.52 (0.352)	0.52 (0.466)	0.58 (0.087)	0.57 (0.064)	0.61 (0.138)	0.63 (0.202)	0.63 (0.289)	0.65 (0.298)
Zinc	0.51 (0.581)	**0.53 (0.252)**	**0.58 (0.018)**	**0.57 (0.019)**	**0.61 (0.002)**	**0.62 (0.004)**	0.60 (0.019)	0.57 (0.034)	0.58 (0.122)
Nickel	0.50 (0.500)	0.49 (0.541)	0.48 (0.635)	**0.53 (0.159)**	**0.56 (0.009)**	**0.53 (0.130)**	**0.52 (0.152)**	**0.60 (0.014)**	**0.62 (0.000)**
Tin	0.47 (0.843)	**0.51 (0.417)**	**0.52 (0.101)**	**0.55 (0.007)**	**0.56 (0.000)**	**0.55 (0.000)**	**0.60 (0.000)**	**0.59 (0.000)**	**0.56 (0.000)**
Corn	**0.59 (0.009)**	0.62 (0.001)	**0.66 (0.001)**	**0.58 (0.050)**	0.51 (0.443)	0.51 (0.441)	**0.57 (0.117)**	**0.57 (0.063)**	0.58 (0.035)
Soybeans	**0.58 (0.015)**	**0.60 (0.012)**	**0.62 (0.011)**	**0.64 (0.007)**	**0.61 (0.023)**	**0.59 (0.110)**	**0.57 (0.083)**	**0.60 (0.041)**	**0.63 (0.002)**
Wheat	**0.61 (0.000)**	**0.64 (0.001)**	**0.59 (0.023)**	**0.52 (0.547)**	0.48 (0.870)	0.48 (0.758)	0.53 (0.437)	0.54 (0.462)	**0.56 (0.269)**

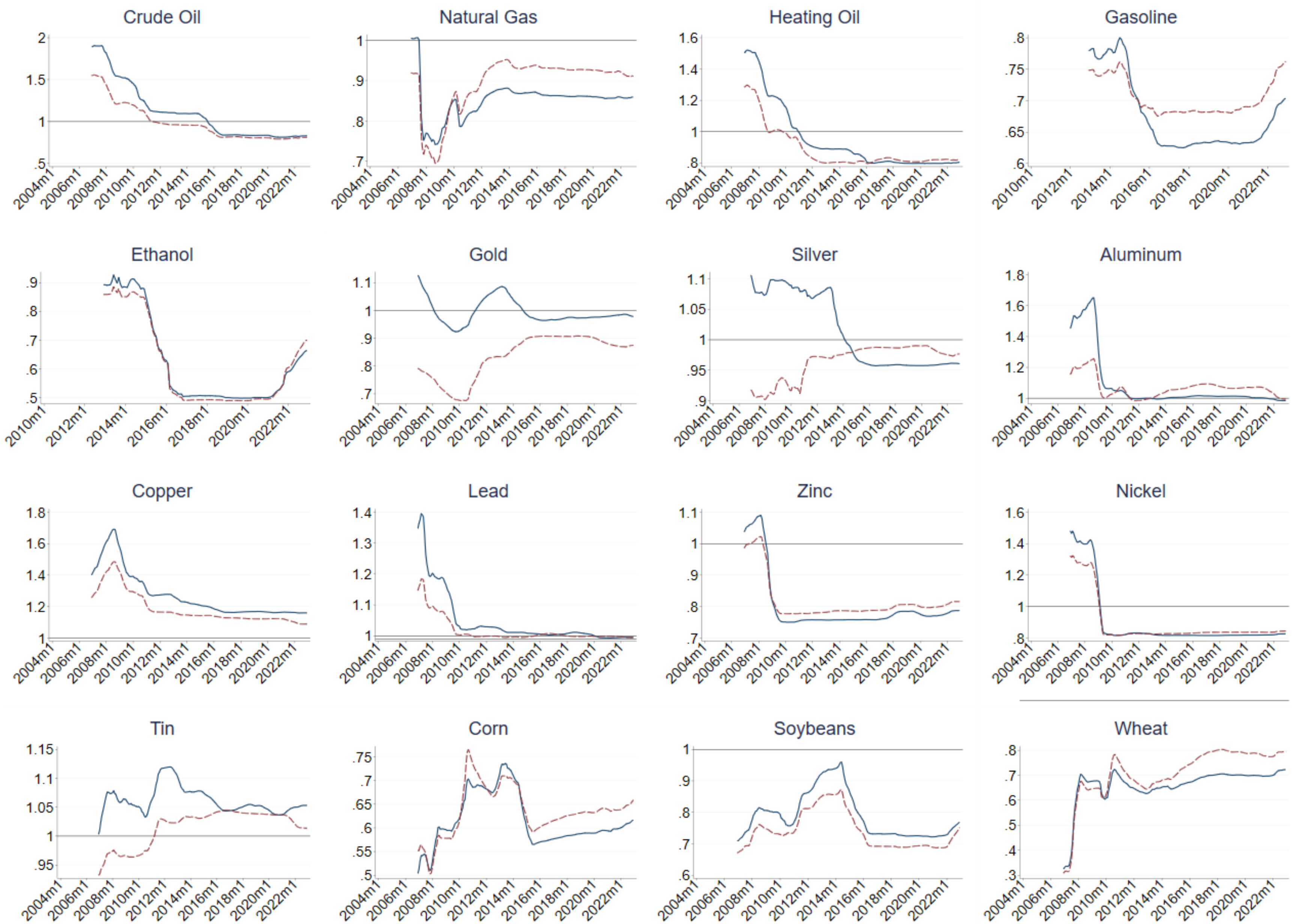
Note: Futures-based forecasts of monthly average spot prices by the end-of-month futures prices (EOM), January 2000–2023. The exception is gasoline and ethanol, which begins in January 2008. Bold values represent improvements over the baseline results in Table 4. The values in the brackets are the p-values for the null hypothesis of equal MSFE ratios based on the DM-test (Diebold and Mariano, 1995) and directional accuracy based on Pesaran and Timmermann (2009).

Figure A1. Evolution of MSFEs Criteria For Futures-Based Forecasts, One-Year Ahead.



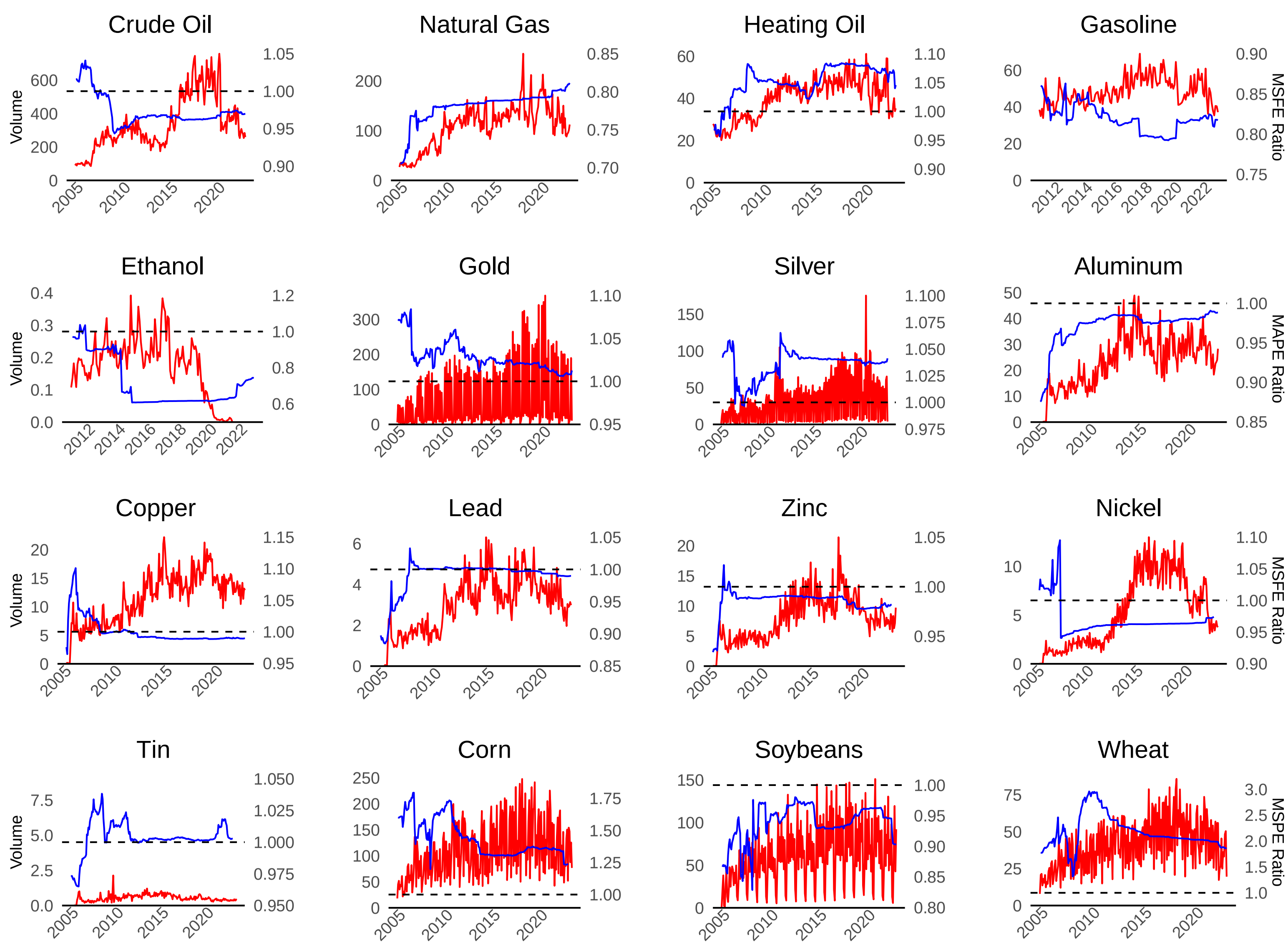
Note: The blue line represents forecasts of real prices using End-of-Month (EoM) futures, while the red line illustrates forecasts of real prices utilizing average futures. A horizontal reference line is drawn at the value of 1 to serve as a benchmark for evaluating MSFE values, which are reported relative to the average price of a no-change forecast.

Figure A2. Evolution of MSFEs Criteria For Futures-Based Forecasts, Two-Year Ahead.



Note: The blue line represents forecasts of real prices using End-of-Month (EoM) futures, while the red line illustrates forecasts of real prices utilizing average futures. A horizontal reference line is drawn at the value of 1 to serve as a benchmark for evaluating MSFE values, which are reported relative to the average price of a no-change forecast.

Figure A3. Traded Volume vs MSFE Ratio for the One-Month Ahead.



Note: The blue line represents the MSFE Ratio, whereas the red line represents the trading volume (Thousands) of the corresponding commodity for the front contract.

B.4 Direct Forecasts

Table A.5. Direct Futures-based Forecasts of Monthly Average Real Prices, Non-Parametric, End-of-Month Futures

	1	3	6	9	12	15	18	21	24
Commodity					MSFE Ratio				
Crude Oil	0.99 (0.305)	0.94 (0.020)	0.88 (0.034)	0.86 (0.060)	0.82 (0.048)	0.77 (0.018)	0.72 (0.010)	0.68 (0.005)	0.63 (0.002)
Natural Gas	1.02 (0.653)	1.00 (0.527)	**0.96 (0.360)**	1.05 (0.626)	1.05 (0.631)	0.97 (0.411)	0.98 (0.436)	0.98 (0.443)	0.98 (0.460)
Heating Oil	1.04 (0.779)	0.98 (0.353)	0.96 (0.217)	0.91 (0.040)	**0.86 (0.005)**	0.85 (0.001)	**0.81 (0.000)**	0.78 (0.000)	**0.73 (0.000)**
Gasoline	0.81 (0.004)	0.74 (0.001)	0.69 (0.003)	0.81 (0.031)	**0.87 (0.055)**	**0.80 (0.015)**	0.74 (0.005)	0.73 (0.004)	0.69 (0.001)
Ethanol	**0.71 (0.106)**	**0.67 (0.057)**	**0.73 (0.103)**	**0.75 (0.086)**	**0.71 (0.067)**	**0.67 (0.033)**	**0.65 (0.031)**	**0.61 (0.031)**	**0.57 (0.021)**
Gold	1.01 (0.604)	1.00 (0.424)	1.00 (0.509)	0.99 (0.403)	0.98 (0.343)	0.97 (0.285)	0.96 (0.224)	0.95 (0.158)	0.93 (0.117)
Silver	1.04 (0.884)	1.00 (0.492)	0.99 (0.287)	0.98 (0.156)	0.97 (0.123)	0.96 (0.076)	0.93 (0.029)	0.90 (0.018)	0.87 (0.016)
Platinum	1.02 (0.859)	0.98 (0.066)	0.93 (0.008)	0.91 (0.010)	0.89 (0.008)	0.88 (0.001)	0.86 (0.000)	0.85 (0.000)	0.86 (0.000)
Aluminum	1.00 (0.526)	1.01 (0.648)	0.98 (0.252)	0.95 (0.119)	0.96 (0.078)	0.96 (0.109)	0.97 (0.163)	0.97 (0.199)	0.96 (0.181)
Copper	0.98 (0.042)	0.98 (0.169)	0.97 (0.118)	0.94 (0.087)	0.94 (0.073)	0.92 (0.061)	0.90 (0.040)	0.88 (0.037)	0.88 (0.056)
Lead	0.97 (0.035)	0.97 (0.008)	0.93 (0.008)	0.87 (0.010)	0.86 (0.009)	0.86 (0.022)	0.84 (0.029)	0.83 (0.013)	0.81 (0.010)
Zinc	0.97 (0.096)	0.95 (0.083)	0.93 (0.080)	0.90 (0.029)	0.90 (0.049)	0.92 (0.090)	0.92 (0.121)	0.92 (0.159)	0.93 (0.227)
Nickel	1.00 (0.632)	1.00 (0.526)	0.98 (0.143)	0.96 (0.106)	0.94 (0.097)	0.90 (0.046)	0.85 (0.022)	0.82 (0.011)	0.80 (0.007)
Tin	1.00 (0.503)	1.02 (0.689)	1.02 (0.607)	1.00 (0.507)	0.98 (0.408)	0.95 (0.226)	0.95 (0.192)	0.98 (0.337)	0.99 (0.439)
Corn	1.05 (0.622)	0.76 (0.054)	0.68 (0.028)	0.70 (0.040)	0.71 (0.046)	0.68 (0.032)	0.64 (0.026)	0.62 (0.022)	0.58 (0.009)
Soybeans	0.86 (0.130)	0.77 (0.037)	0.74 (0.029)	0.78 (0.044)	**0.83 (0.122)**	0.77 (0.100)	0.72 (0.064)	**0.71 (0.053)**	0.68 (0.026)
Wheat	1.11 (0.922)	1.07 (0.779)	1.03 (0.588)	0.99 (0.481)	0.97 (0.436)	0.96 (0.407)	0.96 (0.340)	0.95 (0.280)	0.90 (0.203)
					Success Ratio				
Crude Oil	0.55 (0.091)	0.52 (0.208)	0.58 (0.093)	0.62 (0.031)	0.68 (0.002)	0.69 (0.000)	0.66 (0.002)	0.64 (0.005)	0.75 (0.000)
Natural Gas	0.52 (0.321)	0.54 (0.169)	0.61 (0.000)	0.63 (0.004)	0.64 (0.006)	0.66 (0.003)	0.63 (0.017)	0.64 (0.006)	0.62 (0.021)
Heating Oil	0.52 (0.300)	0.56 (0.072)	0.61 (0.019)	0.69 (0.000)	0.77 (0.000)	0.82 (0.000)	0.81 (0.000)	0.83 (0.000)	0.81 (0.000)
Gasoline	0.62 (0.001)	0.62 (0.004)	0.71 (0.000)	0.65 (0.001)	0.62 (0.001)	0.62 (0.001)	0.65 (0.002)	0.69 (0.000)	0.70 (0.000)
Ethanol	0.55 (0.086)	0.59 (0.015)	0.66 (0.000)	0.64 (0.001)	0.64 (0.024)	0.69 (0.000)	0.64 (0.001)	0.68 (0.000)	0.73 (0.000)
Gold	0.47 (0.444)	0.55 (0.114)	0.48 (0.170)	0.54 (0.140)	0.52 (0.616)	0.57 (0.000)	0.55 (0.000)	0.56 (0.000)	0.50 (0.000)
Silver	0.47 (0.753)	0.50 (0.779)	0.59 (0.353)	0.66 (0.069)	0.67 (0.037)	0.66 (0.004)	0.67 (0.000)	0.67 (0.000)	0.63 (0.009)
Platinum	0.49 (0.370)	0.56 (0.238)	0.66 (0.016)	0.64 (0.114)	0.72 (0.011)	0.76 (0.002)	0.79 (0.000)	0.82 (0.000)	0.84 (0.000)
Aluminum	0.47 (0.702)	0.45 (0.862)	0.46 (0.682)	0.47 (0.598)	0.50 (0.466)	0.49 (0.504)	0.53 (0.235)	0.56 (0.061)	0.56 (0.064)
Copper	0.53 (0.024)	0.53 (0.000)	0.60 (1.000)	0.61 (1.000)	0.63 (1.000)	0.63 (1.000)	0.60 (1.000)	0.59 (1.000)	0.59 (1.000)
Lead	0.56 (0.060)	0.61 (0.005)	0.60 (0.057)	0.62 (0.020)	0.58 (0.011)	0.65 (0.009)	0.66 (0.144)	0.65 (0.080)	0.67 (0.061)
Zinc	0.53 (0.519)	0.50 (0.548)	0.52 (0.346)	0.51 (0.344)	0.57 (0.086)	0.61 (0.021)	0.60 (0.020)	0.59 (0.012)	0.58 (0.120)
Nickel	0.50 (1.000)	0.49 (0.290)	0.50 (0.069)	0.50 (0.500)	0.50 (0.000)	0.50 (0.000)	0.49 (0.000)	0.56 (0.000)	0.55 (0.000)
Tin	0.53 (1.000)	0.50 (1.000)	0.48 (1.000)	0.52 (1.000)	0.52 (1.000)	0.54 (1.000)	0.58 (1.000)	0.57 (1.000)	0.54 (1.000)
Corn	0.56 (0.028)	0.63 (0.001)	0.64 (0.004)	0.57 (0.110)	0.51 (0.444)	0.52 (0.355)	0.55 (0.177)	0.56 (0.093)	0.59 (0.024)
Soybeans	0.56 (0.051)	0.53 (0.260)	0.60 (0.021)	0.63 (0.012)	0.58 (0.074)	0.58 (0.150)	0.55 (0.144)	0.58 (0.087)	0.62 (0.004)
Wheat	0.55 (0.088)	0.56 (0.075)	0.58 (0.034)	0.49 (0.840)	0.48 (0.881)	0.49 (0.733)	0.53 (0.441)	0.54 (0.485)	0.55 (0.371)

Note: Forecast performance of forecasting regressions using the futures-spot spread, without relying on log-approximations, January 2010–2023. The bold values represent improvements over the baseline results in Table 4. The values in the brackets are the p-values for the null hypothesis of equal MSFE ratios based on the DM-test (Diebold and Mariano, 1995) and random directional accuracy following Pesaran and Timmermann (2009).

B.5 Comparison of Contract and Horizon Alignment Assumptions

Table A.6. Adjustment Variations in First-Month Futures Forecasting, Non-Parametric

	Baseline	No Adjustment	Adjustment (1)	Adjustment (2)	Adjustment (3)	Adjustment (4)
Commodity			MSFE Ratio			
Crude Oil	0.99 (0.313)	0.99 (0.263)	1.00 (0.504)	0.99 (0.159)	1.00 (0.552)	0.99 (0.313)
Natural Gas	1.02 (0.663)	1.18 (0.923)	1.07 (0.829)	1.02 (0.663)	1.27 (0.965)	1.23 (0.922)
Heating Oil	1.04 (0.767)	1.29 (0.954)	1.04 (0.767)	1.06 (0.761)	1.23 (0.961)	1.37 (0.978)
Gasoline	0.81 (0.004)	0.90 (0.058)	0.81 (0.004)	0.92 (0.006)	0.81 (0.022)	0.98 (0.386)
Ethanol	0.72 (0.125)	1.18 (0.663)	0.72 (0.125)	0.80 (0.105)	1.27 (0.717)	1.22 (0.705)
Corn	1.03 (0.580)	1.25 (0.949)	0.93 (0.321)	0.97 (0.339)	1.03 (0.580)	1.49 (0.994)
Soybeans	0.86 (0.125)	0.95 (0.266)	0.83 (0.075)	0.93 (0.036)	0.86 (0.125)	1.12 (0.957)
Wheat	1.10 (0.911)	1.21 (0.985)	1.14 (0.968)	1.01 (0.648)	1.10 (0.911)	1.20 (0.983)
			Success Ratio			
Crude Oil	0.55 (0.091)	0.51 (0.166)	0.51 (0.344)	0.49 (0.195)	0.51 (0.353)	0.55 (0.091)
Natural Gas	0.52 (0.321)	0.53 (0.284)	0.56 (0.081)	0.52 (0.321)	0.51 (0.402)	0.53 (0.203)
Heating Oil	0.52 (0.300)	0.51 (0.470)	0.52 (0.300)	0.52 (0.325)	0.50 (0.566)	0.49 (0.688)
Gasoline	0.62 (0.001)	0.56 (0.029)	0.62 (0.001)	0.60 (0.001)	0.62 (0.000)	0.53 (0.278)
Ethanol	0.55 (0.086)	0.63 (0.001)	0.55 (0.086)	0.64 (0.000)	0.56 (0.033)	0.64 (0.000)
Corn	0.56 (0.028)	0.55 (0.145)	0.58 (0.008)	0.55 (0.088)	0.56 (0.028)	0.55 (0.076)
Soybeans	0.56 (0.051)	0.60 (0.006)	0.54 (0.183)	0.53 (0.269)	0.56 (0.051)	0.56 (0.004)
Wheat	0.55 (0.088)	0.53 (0.164)	0.57 (0.012)	0.56 (0.031)	0.55 (0.088)	0.56 (0.075)

Note: Futures-Based Forecasts of nominal monthly prices by EoM Futures Curve, from January 2010 to 2023, for one month ahead. Bold values indicate improvements over the forecast with no end-of-month adjustments. "Baseline" is the adjustment assumptions detailed in section 4.2 used as the baseline in the main tables. "No Adjustment" uses the front-month contract. "Adjustment (1)" omits the front-month contract and averages the spot with the second-month contract. "Adjustment (2)" assigns the front contract with the two-month ahead and averages the spot with the front contract. "Adjustment (3)" calculates the average of the first and second front contracts after aligning them with their corresponding horizons. Lastly, "Adjustment (4)" applies the average curvature from the first 12 contracts to the first contract. This table includes only the commodities for which the front-month contracts do not correspond with the one-month ahead forecast, in line with the assumptions explained in section **??**.

B.6 Assessing Seasonality in Futures-Based Forecast Errors

Table A.7. F Statistics and P-Values for Seasonality Tests in Forecast Errors

Commodity	1	3	6	9	12	15	18	21	24
Crude Oil	0.632 (0.799)	0.511 (0.894)	0.696 (0.741)	0.439 (0.936)	0.092 (1.000)	0.094 (1.000)	0.149 (0.999)	0.104 (1.000)	0.040 (1.000)
Natural Gas	1.123 (0.348)	1.110 (0.357)	1.269 (0.248)	0.883 (0.559)	0.515 (0.891)	0.422 (0.944)	0.381 (0.961)	0.332 (0.977)	0.277 (0.989)
Heating Oil	0.941 (0.503)	0.572 (0.849)	0.358 (0.970)	0.212 (0.997)	0.065 (1.000)	0.075 (1.000)	0.066 (1.000)	0.090 (1.000)	0.038 (1.000)
Gasoline	1.124 (0.347)	0.477 (0.915)	0.640 (0.792)	0.413 (0.948)	0.125 (1.000)	0.096 (1.000)	0.166 (0.999)	0.098 (1.000)	0.050 (1.000)
Ethanol	1.663 (0.087)	0.760 (0.679)	0.866 (0.575)	0.597 (0.829)	0.655 (0.778)	0.603 (0.824)	0.862 (0.579)	0.708 (0.729)	0.554 (0.862)
Gold	1.247 (0.262)	0.972 (0.475)	0.156 (0.999)	0.320 (0.981)	0.048 (1.000)	0.234 (0.995)	0.097 (1.000)	0.138 (1.000)	0.079 (1.000)
Silver	1.016 (0.435)	0.879 (0.563)	0.145 (0.999)	0.234 (0.995)	0.047 (1.000)	0.187 (0.998)	0.092 (1.000)	0.213 (0.996)	0.069 (1.000)
Palladium	1.551 (0.120)	1.048 (0.408)	0.651 (0.782)	0.427 (0.942)	0.021 (1.000)	0.121 (1.000)	0.142 (0.999)	0.140 (1.000)	0.087 (1.000)
Platinum	**2.799 (0.002)**	**2.134 (0.021)**	1.000 (0.450)	0.778 (0.662)	0.085 (1.000)	0.666 (0.768)	0.364 (0.967)	0.520 (0.887)	0.059 (1.000)
Aluminum	1.736 (0.071)	1.360 (0.198)	0.639 (0.793)	0.309 (0.983)	0.032 (1.000)	0.106 (1.000)	0.046 (1.000)	0.061 (1.000)	0.018 (1.000)
Copper	1.590 (0.107)	1.593 (0.106)	1.214 (0.283)	0.366 (0.967)	0.052 (1.000)	0.091 (1.000)	0.138 (1.000)	0.093 (1.000)	0.036 (1.000)
Lead	1.274 (0.245)	1.168 (0.314)	0.849 (0.591)	0.468 (0.920)	0.031 (1.000)	0.120 (1.000)	0.156 (0.999)	0.235 (0.995)	0.025 (1.000)
Zinc	1.500 (0.137)	1.325 (0.216)	0.946 (0.499)	0.430 (0.940)	0.077 (1.000)	0.086 (1.000)	0.177 (0.999)	0.153 (0.999)	0.040 (1.000)
Nickel	1.373 (0.192)	1.181 (0.305)	0.676 (0.760)	0.337 (0.976)	0.056 (1.000)	0.234 (0.995)	0.103 (1.000)	0.112 (1.000)	0.051 (1.000)
Tin	**2.318 (0.012)**	**2.330 (0.011)**	1.433 (0.164)	0.644 (0.788)	0.129 (1.000)	0.111 (1.000)	0.229 (0.995)	0.259 (0.992)	0.036 (1.000)
Corn	1.516 (0.132)	0.604 (0.823)	0.618 (0.811)	0.259 (0.992)	0.225 (0.996)	0.239 (0.994)	0.100 (1.000)	0.066 (1.000)	0.182 (0.998)
Soybeans	1.344 (0.206)	0.763 (0.676)	0.820 (0.620)	0.503 (0.899)	0.318 (0.981)	0.356 (0.970)	0.347 (0.973)	0.248 (0.993)	0.239 (0.994)
Wheat	0.572 (0.849)	0.163 (0.999)	0.200 (0.997)	0.115 (1.000)	0.076 (1.000)	0.169 (0.999)	0.104 (1.000)	0.085 (1.000)	0.022 (1.000)

Note: This table presents the F statistics from the joint significance test of monthly dummies, where we regress the forecast errors of futures-based forecasts against monthly dummies. Numbers in brackets are the corresponding p-values. Values highlighted in bold indicate statistical significance at the 5% level.

B.7 Parametric Models

Table A.8. MSFE Precision of Futures-based Forecasts of Monthly Real Prices, Parametric

		1	3	6	12	15	18	24
Commodity	Model				MSFE Ratio			
Crude Oil	$\hat{\alpha}$	27.89 (1.000)	4.29 (1.000)	2.15 (0.997)	1.31 (0.825)	1.03 (0.540)	0.83 (0.256)	0.64 (0.049)
	$\hat{\beta}$	1.00 (0.147)	1.00 (0.009)	0.98 (0.014)	0.95 (0.027)	0.91 (0.010)	0.88 (0.007)	0.82 (0.002)
	$\hat{\alpha}, \hat{\beta}$	1.00 (0.577)	1.05 (0.939)	1.06 (0.922)	1.17 (0.986)	1.09 (0.951)	1.09 (0.971)	1.17 (0.981)
Natural Gas	$\hat{\alpha}$	4.41 (1.000)	1.63 (0.969)	1.38 (0.891)	1.31 (0.844)	1.13 (0.753)	1.12 (0.748)	1.10 (0.717)
	$\hat{\beta}$	1.00 (0.166)	**0.97 (0.036)**	**0.95 (0.190)**	1.06 (0.684)	1.03 (0.582)	1.07 (0.662)	1.12 (0.738)
	$\hat{\alpha}, \hat{\beta}$	1.11 (0.970)	1.07 (0.717)	1.27 (0.879)	1.60 (0.923)	1.29 (0.874)	1.22 (0.857)	1.19 (0.836)
Heating Oil	$\hat{\alpha}$	24.26 (1.000)	4.78 (1.000)	2.58 (1.000)	1.29 (0.900)	1.06 (0.635)	0.91 (0.279)	**0.73 (0.025)**
	$\hat{\beta}$	1.00 (0.184)	0.99 (0.096)	0.99 (0.037)	0.96 (0.003)	0.94 (0.001)	0.92 (0.000)	0.86 (0.000)
	$\hat{\alpha}, \hat{\beta}$	1.01 (0.856)	1.02 (0.926)	1.05 (0.940)	1.09 (0.969)	1.06 (0.884)	1.02 (0.713)	1.03 (0.695)
Gasoline	$\hat{\alpha}$	3.84 (1.000)	1.12 (0.743)	0.84 (0.171)	1.04 (0.600)	0.96 (0.382)	0.85 (0.102)	0.83 (0.070)
	$\hat{\beta}$	0.98 (0.004)	0.82 (0.001)	0.75 (0.014)	0.90 (0.104)	0.87 (0.137)	0.81 (0.140)	0.71 (0.040)
	$\hat{\alpha}, \hat{\beta}$	1.06 (0.770)	1.25 (0.898)	1.18 (0.760)	1.49 (0.958)	1.80 (0.991)	1.62 (0.959)	1.77 (0.956)
Ethanol	$\hat{\alpha}$	2.11 (0.963)	1.17 (0.709)	1.12 (0.640)	0.81 (0.254)	0.74 (0.158)	0.72 (0.132)	0.67 (0.103)
	$\hat{\beta}$	0.87 (0.036)	**0.69 (0.021)**	0.98 (0.481)	0.90 (0.369)	**0.69 (0.087)**	**0.65 (0.055)**	0.81 (0.115)
	$\hat{\alpha}, \hat{\beta}$	0.85 (0.122)	0.75 (0.079)	1.19 (0.667)	0.96 (0.447)	0.78 (0.189)	0.82 (0.232)	0.99 (0.483)
Gold	$\hat{\alpha}$	113.54 (1.000)	22.41 (1.000)	10.77 (1.000)	5.41 (1.000)	4.30 (1.000)	3.61 (1.000)	2.85 (1.000)
	$\hat{\beta}$	1.00 (0.644)	1.00 (0.333)	1.00 (0.124)	1.00 (0.010)	1.00 (0.001)	1.00 (0.001)	0.99 (0.007)
	$\hat{\alpha}, \hat{\beta}$	1.02 (0.777)	1.20 (0.940)	1.54 (0.969)	2.45 (0.993)	3.00 (0.996)	3.66 (0.997)	5.68 (0.999)
Silver	$\hat{\alpha}$	17.30 (1.000)	4.50 (1.000)	2.38 (1.000)	1.42 (0.942)	1.25 (0.846)	1.14 (0.714)	0.91 (0.363)
	$\hat{\beta}$	1.00 (0.375)	1.00 (0.178)	1.00 (0.048)	1.00 (0.022)	1.00 (0.017)	0.99 (0.007)	0.98 (0.007)
	$\hat{\alpha}, \hat{\beta}$	1.03 (0.890)	1.17 (0.931)	1.45 (0.954)	2.03 (0.989)	2.42 (0.995)	3.27 (0.997)	4.92 (0.998)
Platinum	$\hat{\alpha}$	61.05 (1.000)	11.37 (1.000)	5.82 (1.000)	2.36 (0.997)	1.70 (0.951)	1.27 (0.762)	**0.74 (0.197)**
	$\hat{\beta}$	1.00 (0.718)	1.00 (0.011)	1.00 (0.001)	1.00 (0.000)	0.99 (0.000)	0.99 (0.000)	0.98 (0.000)
	$\hat{\alpha}, \hat{\beta}$	1.02 (0.807)	1.23 (0.986)	1.79 (0.998)	1.77 (0.999)	2.13 (1.000)	2.36 (1.000)	2.91 (1.000)
Aluminum	$\hat{\alpha}$	32.48 (1.000)	5.84 (1.000)	2.95 (1.000)	1.93 (0.994)	1.69 (0.982)	1.56 (0.967)	1.34 (0.898)
	$\hat{\beta}$	1.00 (0.751)	1.00 (0.700)	1.00 (0.238)	1.00 (0.073)	1.00 (0.166)	1.00 (0.273)	1.00 (0.361)
	$\hat{\alpha}, \hat{\beta}$	1.01 (0.844)	1.06 (0.951)	1.13 (0.974)	1.20 (0.997)	1.21 (0.997)	1.20 (0.995)	1.13 (0.893)
Copper	$\hat{\alpha}$	28.93 (1.000)	4.96 (1.000)	2.18 (0.999)	1.21 (0.849)	1.14 (0.801)	1.15 (0.882)	1.44 (1.000)
	$\hat{\beta}$	1.00 (0.950)	1.00 (0.048)	1.00 (0.042)	0.98 (0.019)	0.97 (0.019)	0.96 (0.015)	0.93 (0.033)
	$\hat{\alpha}, \hat{\beta}$	1.03 (0.929)	1.23 (0.958)	1.62 (0.984)	2.47 (0.999)	2.84 (1.000)	3.24 (1.000)	4.23 (1.000)
Lead	$\hat{\alpha}$	21.28 (1.000)	4.55 (1.000)	2.16 (1.000)	1.07 (0.645)	1.00 (0.505)	1.02 (0.566)	1.12 (0.846)
	$\hat{\beta}$	1.00 (0.995)	1.00 (0.001)	0.99 (0.006)	0.96 (0.007)	0.94 (0.017)	0.92 (0.024)	0.86 (0.007)
	$\hat{\alpha}, \hat{\beta}$	1.03 (0.909)	1.25 (0.969)	1.71 (0.981)	2.81 (0.997)	3.21 (0.999)	4.11 (1.000)	6.17 (1.000)
Zinc	$\hat{\alpha}$	22.68 (1.000)	4.86 (1.000)	2.49 (1.000)	1.62 (0.985)	1.43 (0.964)	1.28 (0.920)	1.12 (0.788)
	$\hat{\beta}$	1.00 (0.971)	1.00 (0.043)	0.99 (0.043)	0.97 (0.029)	0.96 (0.052)	0.95 (0.069)	0.93 (0.161)
	$\hat{\alpha}, \hat{\beta}$	1.00 (0.422)	1.08 (0.992)	1.19 (0.989)	1.35 (0.998)	1.36 (0.999)	1.30 (0.999)	1.14 (0.965)
Nickel	$\hat{\alpha}$	9.79 (1.000)	2.25 (1.000)	1.39 (0.935)	1.25 (0.991)	1.40 (0.999)	1.58 (0.999)	1.82 (0.999)
	$\hat{\beta}$	1.00 (0.283)	1.00 (0.304)	0.99 (0.094)	**0.93 (0.067)**	**0.84 (0.037)**	**0.76 (0.020)**	**0.69 (0.007)**
	$\hat{\alpha}, \hat{\beta}$	1.01 (0.734)	1.07 (0.958)	1.16 (0.944)	1.36 (0.993)	1.45 (0.999)	1.56 (1.000)	1.74 (1.000)
Tin	$\hat{\alpha}$	17.68 (1.000)	2.85 (0.999)	1.41 (0.858)	1.17 (0.785)	1.11 (0.770)	1.10 (0.805)	1.18 (0.979)
	$\hat{\beta}$	1.00 (0.228)	1.00 (0.577)	1.00 (0.512)	0.99 (0.302)	0.98 (0.154)	0.97 (0.131)	0.99 (0.284)
	$\hat{\alpha}, \hat{\beta}$	1.05 (0.891)	1.16 (0.919)	1.33 (0.957)	1.66 (0.990)	1.85 (0.994)	2.23 (0.997)	3.18 (0.999)
Corn	$\hat{\alpha}$	17.98 (1.000)	3.89 (1.000)	2.21 (0.998)	1.82 (0.985)	1.62 (0.951)	1.47 (0.881)	1.02 (0.520)
	$\hat{\beta}$	1.00 (0.090)	0.98 (0.014)	0.95 (0.015)	0.94 (0.030)	0.90 (0.017)	0.85 (0.011)	0.77 (0.008)
	$\hat{\alpha}, \hat{\beta}$	1.01 (0.740)	1.03 (0.821)	1.05 (0.783)	1.15 (0.997)	1.14 (0.935)	1.15 (0.803)	1.02 (0.530)
Soybeans	$\hat{\alpha}$	32.66 (1.000)	4.78 (1.000)	2.53 (1.000)	2.26 (1.000)	2.01 (0.995)	1.69 (0.973)	1.21 (0.776)
	$\hat{\beta}$	1.00 (0.022)	0.98 (0.016)	0.95 (0.017)	0.91 (0.018)	0.87 (0.017)	0.84 (0.012)	0.78 (0.011)
	$\hat{\alpha}, \hat{\beta}$	1.00 (0.483)	1.02 (0.730)	1.01 (0.564)	1.04 (0.756)	1.08 (0.814)	1.10 (0.865)	1.05 (0.661)
Wheat	$\hat{\alpha}$	29.41 (1.000)	6.58 (1.000)	4.03 (1.000)	2.57 (1.000)	2.35 (0.998)	2.13 (0.990)	1.49 (0.885)
	$\hat{\beta}$	1.00 (0.086)	1.00 (0.210)	**0.99 (0.234)**	0.97 (0.138)	**0.95 (0.086)**	0.94 (0.030)	0.91 (0.037)
	$\hat{\alpha}, \hat{\beta}$	1.02 (0.979)	1.04 (0.994)	1.08 (0.997)	1.05 (0.778)	1.14 (0.776)	1.28 (0.844)	1.28 (0.790)

Notes: Forecast performance of forecasting regressions using the futures-spot spread model, specified in equation 6, January 2010–2023. MSFE ratios are expressed relative to the end-of-month no-change forecast. The bold values represent improvements over the baseline results in Table 4. The values in the brackets are the p-values for the null hypothesis of equal MSFE ratios based on the DM-test (Diebold and Mariano, 1995).

Table A.9. Directional Accuracy of Futures-based Forecasts of Monthly Real Prices, Parametric

		1	3	6	12	15	18	24
Commodity	Model				Success Ratio			
Crude Oil	$\hat{\alpha}$	0.47 (1.000)	0.46 (1.000)	0.46 (0.100)	0.48 (0.100)	0.51 (0.252)	0.49 (0.281)	0.59 (0.000)
	$\hat{\beta}$	0.55 (0.091)	0.52 (0.208)	0.58 (0.093)	0.68 (0.002)	0.69 (0.000)	0.66 (0.002)	0.75 (0.000)
	$\hat{\alpha}, \hat{\beta}$	0.46 (0.934)	0.48 (0.673)	0.49 (0.532)	0.46 (0.732)	0.49 (0.535)	0.41 (0.892)	0.41 (0.873)
Natural Gas	$\hat{\alpha}$	0.50 (0.100)	0.54 (0.000)	**0.64 (0.000)**	0.61 (0.025)	0.60 (0.102)	0.60 (0.103)	0.56 (0.269)
	$\hat{\beta}$	0.52 (0.321)	0.54 (0.169)	0.61 (0.000)	0.64 (0.006)	0.66 (0.003)	0.63 (0.017)	0.62 (0.021)
	$\hat{\alpha}, \hat{\beta}$	0.50 (0.000)	0.54 (0.000)	**0.62 (0.000)**	0.64 (0.001)	0.63 (0.026)	0.60 (0.123)	0.60 (0.140)
Heating Oil	$\hat{\alpha}$	0.49 (1.000)	0.47 (1.000)	0.50 (0.100)	0.50 (0.100)	0.55 (0.000)	0.61 (0.000)	0.60 (0.008)
	$\hat{\beta}$	0.52 (0.300)	0.56 (0.072)	0.61 (0.019)	0.77 (0.000)	0.82 (0.000)	0.81 (0.000)	0.81 (0.000)
	$\hat{\alpha}, \hat{\beta}$	0.48 (0.668)	0.42 (0.924)	0.36 (0.991)	0.40 (0.916)	0.43 (0.827)	0.43 (0.797)	0.43 (0.790)
Gasoline	$\hat{\alpha}$	0.51 (0.000)	0.58 (0.003)	0.64 (0.000)	0.56 (0.014)	0.56 (0.014)	0.58 (0.033)	0.58 (0.000)
	$\hat{\beta}$	0.62 (0.001)	0.62 (0.004)	0.71 (0.000)	0.62 (0.001)	0.62 (0.001)	0.65 (0.002)	0.70 (0.000)
	$\hat{\alpha}, \hat{\beta}$	0.51 (0.000)	0.58 (0.002)	0.59 (0.000)	0.55 (0.050)	0.53 (0.105)	0.55 (0.098)	0.59 (0.000)
Ethanol	$\hat{\alpha}$	0.52 (1.000)	0.57 (0.062)	0.63 (0.000)	**0.65 (0.043)**	0.65 (0.000)	0.57 (0.397)	0.67 (0.000)
	$\hat{\beta}$	0.54 (0.207)	**0.60 (0.024)**	**0.68 (0.000)**	0.63 (0.129)	0.67 (0.000)	0.62 (0.024)	0.73 (0.000)
	$\hat{\alpha}, \hat{\beta}$	0.52 (1.000)	0.56 (0.116)	0.61 (0.000)	0.63 (0.210)	0.65 (0.000)	0.57 (0.397)	0.67 (0.000)
Gold	$\hat{\alpha}$	0.46 (1.000)	0.52 (1.000)	0.46 (1.000)	**0.53 (1.000)**	0.53 (1.000)	0.50 (1.000)	0.45 (1.000)
	$\hat{\beta}$	**0.53 (0.556)**	0.47 (0.630)	**0.52 (0.422)**	**0.58 (0.155)**	**0.70 (0.000)**	**0.67 (0.000)**	0.50 (0.100)
	$\hat{\alpha}, \hat{\beta}$	**0.55 (1.000)**	0.48 (1.000)	**0.54 (1.000)**	0.47 (1.000)	0.47 (1.000)	0.50 (1.000)	**0.55 (1.000)**
Silver	$\hat{\alpha}$	0.48 (1.000)	**0.53 (1.000)**	**0.60 (1.000)**	0.65 (1.000)	0.61 (1.000)	0.58 (1.000)	0.56 (1.000)
	$\hat{\beta}$	0.49 (0.535)	0.50 (0.779)	0.59 (0.353)	0.67 (0.037)	0.66 (0.004)	0.67 (0.000)	0.63 (0.009)
	$\hat{\alpha}, \hat{\beta}$	**0.52 (1.000)**	0.47 (1.000)	0.40 (1.000)	0.35 (1.000)	0.39 (1.000)	0.42 (1.000)	0.44 (1.000)
Platinum	$\hat{\alpha}$	0.47 (1.000)	0.55 (1.000)	0.62 (1.000)	0.69 (1.000)	0.73 (1.000)	0.73 (1.000)	0.79 (1.000)
	$\hat{\beta}$	0.49 (0.370)	0.56 (0.238)	0.66 (0.016)	0.72 (0.011)	0.76 (0.002)	0.79 (0.000)	0.84 (0.000)
	$\hat{\alpha}, \hat{\beta}$	0.44 (1.000)	0.45 (1.000)	0.38 (1.000)	0.31 (1.000)	0.27 (1.000)	0.27 (1.000)	0.21 (1.000)
Aluminum	$\hat{\alpha}$	**0.56 (1.000)**	**0.53 (1.000)**	**0.54 (1.000)**	**0.54 (1.000)**	**0.56 (1.000)**	**0.58 (1.000)**	**0.62 (1.000)**
	$\hat{\beta}$	**0.53 (0.351)**	**0.55 (0.138)**	0.46 (0.682)	0.50 (0.466)	0.49 (0.504)	0.53 (0.235)	0.56 (0.064)
	$\hat{\alpha}, \hat{\beta}$	**0.53 (0.777)**	0.49 (0.615)	0.45 (0.819)	0.40 (0.982)	0.38 (0.999)	0.38 (1.000)	0.50 (0.987)
Copper	$\hat{\alpha}$	0.52 (1.000)	0.53 (1.000)	0.60 (1.000)	0.63 (1.000)	0.63 (0.579)	0.49 (0.901)	0.23 (1.000)
	$\hat{\beta}$	0.47 (0.976)	0.53 (0.000)	0.60 (1.000)	0.63 (1.000)	0.63 (1.000)	0.60 (1.000)	0.59 (1.000)
	$\hat{\alpha}, \hat{\beta}$	0.44 (0.954)	0.46 (1.000)	0.40 (1.000)	0.37 (1.000)	0.37 (1.000)	0.40 (1.000)	0.41 (1.000)
Lead	$\hat{\alpha}$	0.49 (1.000)	0.52 (1.000)	0.54 (1.000)	0.55 (0.000)	0.63 (0.105)	0.63 (0.212)	0.41 (0.974)
	$\hat{\beta}$	0.44 (0.940)	0.61 (0.005)	0.60 (0.057)	0.58 (0.011)	0.65 (0.009)	0.66 (0.144)	0.67 (0.061)
	$\hat{\alpha}, \hat{\beta}$	0.42 (0.971)	0.48 (0.541)	0.46 (1.000)	0.48 (1.000)	0.39 (1.000)	0.35 (1.000)	0.34 (1.000)
Zinc	$\hat{\alpha}$	**0.56 (1.000)**	**0.51 (1.000)**	0.49 (1.000)	0.50 (1.000)	0.53 (1.000)	0.53 (1.000)	0.46 (0.818)
	$\hat{\beta}$	0.46 (0.547)	**0.51 (0.506)**	0.52 (0.346)	0.57 (0.086)	0.61 (0.021)	0.60 (0.020)	0.58 (0.120)
	$\hat{\alpha}, \hat{\beta}$	**0.56 (0.830)**	0.46 (0.763)	0.46 (1.000)	0.49 (1.000)	0.40 (0.995)	0.37 (0.986)	0.42 (0.881)
Nickel	$\hat{\alpha}$	0.50 (1.000)	0.49 (1.000)	0.49 (1.000)	0.38 (0.980)	0.24 (1.000)	0.23 (1.000)	0.34 (1.000)
	$\hat{\beta}$	0.50 (1.000)	0.49 (0.290)	0.50 (0.569)	0.50 (1.000)	0.50 (1.000)	0.49 (1.000)	0.55 (0.000)
	$\hat{\alpha}, \hat{\beta}$	**0.51 (0.321)**	0.45 (0.814)	0.34 (0.998)	0.35 (0.990)	0.28 (1.000)	0.32 (0.995)	0.16 (1.000)
Tin	$\hat{\alpha}$	0.53 (1.000)	0.50 (1.000)	0.48 (1.000)	0.52 (1.000)	0.54 (1.000)	0.55 (0.950)	0.47 (0.736)
	$\hat{\beta}$	0.53 (1.000)	0.50 (1.000)	0.48 (1.000)	0.52 (1.000)	0.54 (1.000)	0.58 (1.000)	0.54 (1.000)
	$\hat{\alpha}, \hat{\beta}$	0.44 (0.937)	0.49 (1.000)	**0.52 (1.000)**	0.48 (1.000)	0.47 (1.000)	0.42 (1.000)	0.46 (1.000)
Corn	$\hat{\alpha}$	0.48 (1.000)	0.48 (1.000)	0.48 (1.000)	0.50 (1.000)	0.51 (1.000)	0.53 (1.000)	0.58 (1.000)
	$\hat{\beta}$	0.55 (0.127)	**0.64 (0.000)**	**0.65 (0.001)**	**0.52 (0.404)**	0.50 (0.486)	0.55 (0.177)	0.58 (0.035)
	$\hat{\alpha}, \hat{\beta}$	0.42 (0.999)	0.44 (0.994)	0.47 (0.851)	0.44 (0.827)	0.49 (1.000)	0.52 (1.000)	0.59 (0.000)
Soybeans	$\hat{\alpha}$	0.51 (1.000)	0.46 (1.000)	0.49 (1.000)	0.50 (1.000)	0.53 (1.000)	0.49 (1.000)	0.53 (1.000)
	$\hat{\beta}$	0.55 (0.147)	0.53 (0.251)	0.60 (0.023)	0.57 (0.091)	0.58 (0.150)	**0.56 (0.117)**	0.61 (0.034)
	$\hat{\alpha}, \hat{\beta}$	0.48 (0.991)	0.45 (0.923)	0.48 (0.751)	0.49 (0.559)	0.53 (0.453)	0.48 (0.585)	0.53 (0.000)
Wheat	$\hat{\alpha}$	0.51 (1.000)	0.50 (1.000)	0.48 (1.000)	0.45 (1.000)	0.49 (1.000)	0.47 (1.000)	0.50 (1.000)
	$\hat{\beta}$	0.55 (0.069)	**0.57 (0.057)**	0.58 (0.033)	0.50 (0.774)	0.49 (0.659)	0.53 (0.441)	**0.56 (0.269)**
	$\hat{\alpha}, \hat{\beta}$	0.45 (0.937)	0.42 (0.956)	0.34 (1.000)	0.46 (1.000)	0.49 (0.100)	0.49 (1.000)	0.50 (1.000)

Notes: Forecast performance of forecasting regressions using the futures-spot spread model, specified in equation 6, January 2010–2023. Bold values represent improvements over the baseline results in Table 4. P-values in parentheses.

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