Does Speculation in Futures Markets Improve Commodity Hedging Decisions?

Adrian Fernandez-Perez†, Ana-Maria Fuertes‡ and Joëlle Miffre§

Abstract

This article performs a comparative analysis of traditional and selective hedging strategies in commodity futures markets. Traditional hedging solely seeks to minimize risk, while selective hedging simultaneously pursues economic gains by predicting futures returns. The predictions, in turn, range from naïve historical averages to sophisticated forecasts based on, for example, style integration or machine learning. We compare the effectiveness of the various hedges in terms of their ability to maximize expected utility. An out-of-sample analysis applied to 24 commodities endorses traditional over selective hedging, as the latter increases risk but fails to capture alpha. The findings survive different specifications of the traditional and selective hedges, longer estimation windows, alternative rebalancing frequencies, inter alia.

Keywords: Traditional hedging; Selective hedging; Expected utility; Commodity futures markets; Machine learning

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† Senior Research Fellow, Auckland University of Technology, Private Bag 92006, 1142 Auckland, New Zealand; Tel: +64 9 921 9999; E-mail: adrian.fernandez@aut.ac.nz

‡ Professor of Finance and Econometrics, Bayes Business School, City, University of London, ECIY 8TZ, England; Tel: +44 (0)20 7040 0186; E-mail: a.fuertes@city.ac.uk

§ Professor of Finance, Audencia Business School, 8 Route de la Jonelière, 44312, Nantes, France; Tel: +33 (0)2 40 37 34 34, E-mail: jmiffre@audencia.com; Louis Bachelier Fellow and Corresponding author

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1. Introduction

While traditional hedging solely aims at minimization spot price risk, selective hedging simultaneously targets economic gains by predicting futures returns. Selective hedging stems as the rational expectation equilibrium solution of extant theoretical models of hedging (Anderson and Danthine, 1981, 1983; Stulz, 1984) and is aligned with the practices of nonfinancial firms. For example, Adam and Fernando (2006) and Brown et al. (2006) argue that the hedge ratios of gold mining companies are too volatile to be explained by a pure hedging rationale; they must therefore contain a speculative component that hinges on managerial predictions about the direction of the futures market (see also Cheng and Xiong, 2014; Carter et al., 2021).

This article uses state-of-the-art advances in time-series predictability to answer the following questions: Shall risk managers adopt traditional hedging strategies that solely aim at covering spot price risk? Can they add value by incorporating their market views into their hedging program? We address these questions by comparing traditional hedges – that target risk minimization and hence, assume no change in the futures price over the hedging horizon – and a menu of selective hedges – that rely on an array of techniques to predict the futures return. We start by deploying a naïve selective hedge where the predicted futures return is the historical average return measured over a past window. We also consider selective hedges whose futures return forecasts are derived from an autoregressive model (Cotter and Hanly, 2010, 2012), a vector autoregressive model (Furió and Torró, 2020), the combination of univariate regression forecasts (Rapach et al., 2010; Gargano and Timmermann, 2014; Hollstein et al., 2021) and style integration (Brandt et al., 2009; Barroso et al., 2022). Additionally, we design selective hedges that make use of machine learning methods, thereby allowing for nonlinearity between the predictors and the forecast returns (Fischer and Krauss, 2018; Gu et al., 2020; Chen et al., 2023; Rad et al., 2023). To the best of our knowledge, the selective hedges based on historical average returns, the combination of univariate regression forecasts, and machine learning forecasts are new to the literature on risk management. Bearing in mind that averaging forecasts mitigates their errors (Chen et al., 2022; Cakici et al., 2023), we complement this analysis by considering selective hedges whose predictions of futures returns equally-weight the aforementioned forecasts.

We implement the traditional and selective hedging strategies on a large sample of 24 commodities spanning all sectors (agriculture, energy, livestock, and metals). We compare the effectiveness of the various hedges out-of-sample in terms of the expected utility gains earned through hedging compared to the no-hedging case. The statistical significance of the expected utility gains is assessed via the McCracken and Valente (2018) test.

Our empirical analysis demonstrates that the expected utility gains of traditional hedging are unsurpassed by those obtained from the comprehensive set of selective hedges considered. Thus, commodity hedgers are better off assuming no change in the futures prices over the hedging horizon, which corroborates the absence of a risk premium at the individual commodity level as documented by Erb and Harvey (2006). According to our findings, the inability of selective hedging to outperform traditional hedging can be attributed to the difficulty of generating out-of-sample forecasts of futures return that are reliable and stable enough to compensate for the significantly higher risks incurred in selective hedging, alongside its higher transaction costs. In further analyses, we confirm that the unsurpassed expected utility gains of traditional hedging are robust to alternative specifications of the traditional and selective hedge ratios, to the consideration of time-varying risk aversion, various sub-samples, longer estimation windows, long versus short hedging, and different rebalancing frequencies.

Overall, the main takeaway from our analysis is that selective hedging that stems as an optimal solution from theoretical models is, in practice, not worthwhile for commodity hedgers as the expected utility gains thus achieved are not superior to those from traditional hedging. To state this differently, risk managers shall solely focus on hedging spot price risk and shall not incorporate their market views into their hedging programs.

Our article contributes to the literature in three ways. By endorsing traditional over selective hedging, our paper adds to the traditional hedging literature that has put forward alternative methods to reduce spot price risk such as the one-to-one hedge, the OLS hedge or more sophisticated variants thereof that allow for various estimations of the return covariance matrix (Ederington, 1979; Figlewski, 1984; Baillie and Myers, 1991; Kroner and Sultan, 1993; Brooks et al., 2002; Wang et al., 2015 inter alia).

Our paper also speaks to the selective hedging literature that builds upon the theoretical models of Anderson and Danthine (1981, 1983) and Stulz (1984) with empirical solutions provided by Cotter and Hanly (2010), (2012), Furió and Torró (2020) and Barroso et al. (2022).[1] Our findings on the superiority of traditional over selective hedging align also with a selective hedging literature that, at best, highlights the very small increases in firm value obtained through selective hedging (Adam

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[1] The empirical studies on selective hedging in commodity markets focus solely on the energy sector, and their goal is to examine the impact on the selective hedging outcome of the assumed risk aversion level, the choice of utility function or seasonality (Cotter and Hanly, 2010, 2012; Furió and Torró, 2020). More recently, Barroso et al. (2022) study the hedging problem of a global equity investor exposed to exchange rate risk and propose a selective hedging solution that predicts the currency expected return by optimally integrating currency characteristics.

and Fernando, 2006; Brown et al., 2006) and, at worst, warns against the perils of poorly structured selective hedging programs (Chalmin, 1987; Pirrong, 1997; Carter et al., 2021).[2]

Finally, our article indirectly contributes to the time-series predictability literature. Most studies deal with the predictability of aggregate (portfolio) returns (such as Rapach et al., 2010 and Rapach and Zhou, 2022, for equities, or Gargano and Timmermann, 2014, for commodities). Except for Hollstein et al. (2021), there is no wide-reaching analysis of time-series return predictability for individual commodities. This exercise is challenging as time-series predictability at the single asset level is arguably more difficult than at the portfolio level (see Gu et al., 2020, for a discussion on the sensible 'no predictability' benchmark in each case, and Erb and Harvey, 2006, who document a zero risk premium at individual commodity level). Further advances on time-series predictability at the asset level will be required before selective hedging can be considered as a worthy exercise.

The remainder of the article unfolds as follows. Sections 2 and 3 introduce the methodology and data, respectively. Section 4 presents the expected utility gains generated by the various hedges and explains the failure of selective hedging. Section 5 presents some robustness checks and finally, Section 6 concludes with a summary.

2. Hedging Framework

2.1. Optimal hedging under mean-variance utility

We consider the hedging problem of a commodity producer who builds a hedge at time *t* and

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[2] For example, Chalmin (1987) links Cook Industries' 1978 bankruptcy to selective hedging and Pirrong (1997) attributes the $1.3 billion losses of Metallgesellschaft in 1993 to excessive speculation in crude oil futures markets. Carter et al. (2021) examines Queensland Sugar Limited's losses, concluding that over-hedging was the culprit. All these case studies share a common lesson: Avoiding speculation in risk management would have prevented substantial losses.

rebalances it at t+1. As in prior studies, we abstract from uncertainty in the producer's output. Let us assume that the hedger's utility function is quadratic or mean-variance, that is,

$$U(\Delta p_{t+1}) = E(\Delta p_{t+1}) - \frac{1}{2}\,\gamma\, Var(\Delta p_{t+1}), \tag{1}$$

where $\Delta p_{t+1} = \Delta s_{t+1} - h_t \Delta f_{t+1}$ is the log return of the hedge portfolio, s_t is the log of the spot price, f_t is the log of the futures price, h_t is the optimal hedge ratio that defines the number of short futures positions per unit of output or spot position, and γ is the hedger's coefficient of relative risk aversion.

The maximization of the hedger's expected utility conditional on the available information set, Ω_t, gives the selective hedge ratio,

$$h_t = \frac{\sigma_{sf,t}}{\sigma_{f,t}^2} - \frac{E_t(\Delta f_{t+1}|\Omega_t)}{\gamma \sigma_{f,t}^2} = \beta_t - \frac{E_t(\Delta f_{t+1}|\Omega_t)}{\gamma \sigma_{f,t}^2}, \tag{2}$$

where $\sigma_{sf,t}$ and $\sigma_{f,t}^2$ are the time t spot-futures return covariance and futures return variance, respectively, and $E_t(\Delta f_{t+1}|\Omega_t)$ is the expected futures return conditional on Ω_t.

Under two distinct scenarios – if the hedger is infinitely risk averse ($\gamma = \infty$) or if she assumes that the futures price f_t follows a pure random walk ($E_t(\Delta f_{t+1}|\Omega_t) = 0$) – the utility-maximizing selective hedge ratio becomes the minimum variance (MinVar) hedge ratio, $h_t = \beta_t$. Otherwise, the selective hedge is made up of a purely risk-minimizing component, β_t, and a purely speculative component, $\frac{E_t(\Delta f_{t+1}|\Omega_t)}{\gamma \sigma_{f,t}^2}$. Thus, a selective hedger who predicts a rise in the futures price over the hedging horizon ($E_t(\Delta f_{t+1}|\Omega_t) > 0$) shall take less short futures positions than under pure hedging, $h_t < \beta_t$. If she anticipates a fall in the futures price ($E_t(\Delta f_{t+1}|\Omega_t) < 0$), she shall short more futures contracts than under pure hedging, $h_t > \beta_t$.

2.2. Alternative selective hedging strategies

Equation (2) makes it clear that selective hedging requires good forecasts of futures returns. A simple approach is to adopt the historical average (HistAve) futures return as forecast, $E_t(\Delta f_{t+1}|\Omega_t) = \frac{1}{L}\sum_{j=0}^{L-1}\Delta f_{t-j}$ where L is the window length. The HistAve selective hedging therefore assumes that future prices follow a random walk process with a drift component. Second, as in Cotter and Hanly (2010, 2012), we deploy the AR selective hedge by fitting an autoregressive model of order 1, AR(1), to the futures return history $\{\Delta f_{t-j}\}_{j=0}^{L-1}$ to construct the forecast as $E_t(\Delta f_{t+1}|\Omega_\mathrm{t}) = \hat{\alpha}_0 + \hat{\alpha}_1\Delta f_t$. Third, as in Furió and Torró (2020), we obtain the VAR selective hedge that hinges on a futures return forecast from a bivariate vector autoregressive VAR(p) model fitted to past futures returns and roll-yields.[3] These three selective hedges have in common that they exploit a very limited information set, Ω_t, to derive the futures return forecast.

Expanding the information set to include K predictors, $\boldsymbol{z}_t = (z_{1t}, z_{2t}, \dots, z_{Kt})'$, we implement the equal-weight combination (EWC) of univariate regression forecasts advocated by e.g., Rapach et al. (2010) and Hollstein et al. (2021) for equities and commodities, respectively. Specifically, the futures return forecast is obtained as $E_t(\Delta f_{t+1}|\Omega_\mathrm{t}) = \boldsymbol{\omega}_t'\Delta\hat{\boldsymbol{f}}_{t+1}$, $\boldsymbol{\omega}_t' = \left(\frac{1}{K}, \dots, \frac{1}{K}\right)$ with $\Delta\hat{f}_{k,t+1} = \hat{\alpha}_0 + \hat{\alpha}_1 z_{k,t}$, $k = 1, \dots, K$.

Inspired by the optimal currency strategy of Barroso et al. (2022), we also deploy a selective hedge that builds on the style-integration literature initiated by Brandt et al. (2009) where asset characteristics are used to proxy the expected returns. The key idea is that the speculative component of the hedge ratio is obtained as an optimal (or utility maximizing) integration of K

[3] By reflecting commodity inventory levels, the roll-yield is able to predict futures returns (Erb and Harvey, 2006; Szymanowska et al., 2014).

predictors $\boldsymbol{z}_t = (z_{1t}, z_{2t}, \dots, z_{Kt})'$ that are specific to commodity i, subject to a constraint that ensures that the selective hedge portfolio does not depart too much from the traditional hedge portfolio (benchmark). Formally, this selective hedge (K-Integr hereafter) is given by $h_t = \beta_t - \boldsymbol{\omega}_t' \boldsymbol{z}_t$ with integration weights $\boldsymbol{\omega}_t$ derived as

$$\max_{\omega_t} E_t\big[U\big(\Delta p_{K-Integr,t+1}\big)\big|\Omega_t\big] = \max_{\omega_t} E_t[U(\Delta s_{t+1} - (\beta_t - \boldsymbol{\omega}_t' \boldsymbol{z}_t)\Delta f_{t+1})|\Omega_t] \quad (3)$$

$$\text{subject to } \sigma\big(\Delta p_{MinVar,t+1} - \Delta p_{K-Integr,t+1}\big) \leq \varsigma,$$

where $U(\cdot)$ is the mean-variance utility function, β_t is the MinVar hedge ratio, $\Delta p_{K-Integr,t+1}$ and $\Delta p_{MinVar,t+1}$ are the time t+1 return of the K-Integr selective hedge and traditional hedge portfolios, respectively, $\sigma(\cdot)$ denotes standard deviation, and ς is the tracking error.[4]

Machine learning, by allowing for complex nonlinear relationships between candidate predictors and target returns, could also assist in the construction of better selective hedges. The forecast return is then defined as $E_t(\Delta f_{t+1}|\Omega_t) = g^*(\boldsymbol{z}_t)$ where Δf_{t+1} is a pooled vector of total returns for the N futures contracts considered, $\boldsymbol{z}_t$ is a matrix of standardized predictors pooled into a panel and $g^*(\cdot)$ is a nonlinear function that maps the predictors at time t to the expected futures return at time t+1. Following the literature on machine learning (Fischer and Krauss, 2018; Gu et al., 2020; Chen et al., 2023; Rad et al., 2023), the function g^* is proxied by a battery of machine learning algorithms that range from random forest (RF) in our main analysis, to deep neural networks (DNN), taken either in isolation or in conjunction with long-short term memory (LSTM) units, in

[4] Strictly speaking, the objective function in Equation (3) is not identical to that in Barroso et al. (2022) as their focus is the hedging problem of a U.S. investor exposed to the risks of a cross-section of currencies. Ours is the canonical hedging problem of a single commodity (e.g., crude oil) producer. Barroso et al. (2022) consider transaction costs and margin requirements as part of their return definition. While we address the impact of transaction costs on expected utility gains, margin requirements are not germane to our analysis as we assume fully-collateralized futures positions.

the robustness section. To our best knowledge, the HistAve, EWC and machine learning selective hedging strategies are new to the literature on risk management. Table 1 lists all the selective hedges considered.

[Insert Table 1 around here]

2.3. Measuring hedging effectiveness

Hedging effectiveness is assessed via the expected utility gain of a given hedge, defined as the difference between the expected utility of the hedge portfolio and that of the unhedged spot position, as follows

$$E_t[\Delta U_{t+1}^{Hedge}] = E_t[U_{t+1}^{Hedge}] - E_t[U_{t+1}^{Spot}], \tag{4}$$

where $E_t\left[U_{t+1}^{Hedge}\right] = E_t[U(\Delta p_{t+1})]$ with Δp_{t+1} the change in value of the hedge portfolio from time t to $t+1$ as defined in Equation (1), and $E_t\left[U_{t+1}^{Spot}\right] = E_t[U(\Delta s_{t+1})]$ with Δs_{t+1} the spot return over the same period. The representative hedger is expected to select the hedging strategy that maximizes her expected utility gain. Unlike other measures of portfolio performance such as the Sharpe ratio, the expected utility gain of the hedge portfolio is a consistent measure of hedging effectiveness because it allows us to embed the same level of risk aversion γ in the hedge ratio construction, Equation (2), as in the appraisal of hedging effectiveness, Equation (4).

We compare statistically the expected utility gains of selective hedging to those of MinVar by deploying the McCracken and Valente (2018) test. The null hypothesis is $H_0\colon \Delta Udiff_i = \Delta U_i - \Delta U_{MinVar} \leq 0$ versus $H_1\colon \Delta Udiff_i = \Delta U_i - \Delta U_{MinVar} > 0$, where ΔU is the expected utility gain as defined in Equation (4) with the subscript i denoting the selective hedging strategy at hand. The inference is based on the stationary bootstrap of Politis and Romano (1994). We generate $B = 500$ bootstrapped time-series from the original data, i.e., $\Delta s_{t+1,b}$, $\Delta f_{t+1,b}$, and the predictors, $z_{t,b}$, using random geometrically-distributed block lengths whose expected value is calculated as in Patton et al. (2009), i.e., $\frac{1}{T^{0.6}}$ with T the commodity-specific sample size as specified in the last column of Table 2. With each of the bootstrap samples, we calculate $\Delta Udiff_{b,i}^{*} = \Delta U_{b,i}^{*} - \Delta U_{b,MinVar}^{*}$ which enables the bootstrap distribution $\left\{\Delta Udiff_{b,i}^{*}\right\}_{b=1}^{B}$. Finally, we demean this distribution before computing the significance p-value for the test statistic $\Delta Udiff_i$.

3. Data

3.1. Commodity spot and futures prices

Our empirical analysis is based on weekly (Monday) spot prices and futures settlement prices for 24 commodities (spanning the agriculture, energy, livestock, and metal sectors) from Barchart (previously Commodity Research Bureau, CRB) and Refinitiv Datastream, respectively. Spot returns are measured as weekly changes in logarithmic spot prices. Assuming full collateralization, futures returns are measured as weekly logarithmic price changes plus the risk-free rate, $\Delta f_{t+1} = \left(f_{T,t+1} - f_{T,t}\right) + rf_{t+1}$ with $f_{T,t}$ the logarithm price of futures contract with maturity T at week t and rf_{t+1} the risk free rate. We use as proxy for the risk-free rate the 1-month US Treasury bill rate from Prof. Kenneth French's website.

Following the commodity literature, we create a continuous futures return series employing the prices of front-end contracts except in maturity months when we roll to the second-nearest contract (see e.g., Erb and Harvey, 2006; Szymanowska et al., 2014; Boons and Prado, 2019). In a robustness test, we use the second (third, fourth, fifth, sixth, respectively) contracts as hedging instrument. In this case, each contract is held up to the last day of the month preceding the maturity of the front-end contract with the position then rolled to the then second (third, fourth, fifth or sixth, respectively) contract.

Table 2 reports descriptive statistics for commodity spot and (front-end) futures returns, alongside their pairwise correlations. Important stylized facts are confirmed such as the absence of a positive risk premium at the individual commodity level (Erb and Harvey, 2006), as well as large heterogeneities as regards return, risk and correlations (or basis risk). The variance of spot returns ranges from 3.06% per annum (p.a.) for gold to 46.98% for natural gas. The expected utility of the spot asset ranges from -121.76% for natural gas to 0.61% for gold, with an average of -22.42%. The basis risk is highest for lean hogs and lowest for gold as suggested by the correlation between spot and futures returns at 0.30 and 0.99, respectively.

[Insert Table 2 around here]

The futures market for natural gas exhibits the lowest return at -33.62% p.a. As made explicit by Equation (2), a producer of natural gas engaged in selective hedging is thus likely to take more short positions than as dictated by the traditional MinVar hedge ($h_t > \beta_t$). The futures on unleaded gas exhibit the highest mean return at 29.38% p.a. which suggests that a producer engaged in selective hedging is likely to take less short futures positions than as dictated by the traditional MinVar hedge ($h_t < \beta_t$). Both cases, over-hedging and under-hedging, respectively, represent deviations from traditional hedging.

3.2. Commodity futures returns predictors

The first three selective hedging strategies referred to as HistAve, AR and VAR are rather sparse with regards to the conditioning information set, Ω_t, used to construct futures return forecasts. HistAve and AR use past futures returns only, while VAR additionally exploits past roll yields. By contrast, the EWC, *K*-Integr and RF selective hedges exploit multiple predictors $\boldsymbol{z}_t = (z_{1t}, z_{2t}, \dots, z_{Kt})'$.

We consider $K = 37$ variables as commodity futures return predictors. The variables, sampled at the weekly frequency, can be classified in two groups. The first group comprises 10 commodity futures characteristics as advocated in the commodity pricing literature (Erb and Harvey, 2006; Miffre and Rallis, 2007; Hong and Yogo, 2012; Asness et al., 2013; Basu and Miffre, 2013; Szymanowska et al., 2014; Fernandez-Perez et al., 2018; Boons and Prado, 2019; Kang et al., 2020; Sakkas and Tessaromatis, 2020; Gu et al., 2023). The second group includes 27 financial, macroeconomic and sentiment indicators from the time-series predictability literature in equity (Rapach et al., 2010) and commodity (Gargano and Timmermann, 2014; Hollstein et al., 2021) markets. Observations on these variables are downloaded from Refinitiv Datastream, the Commodity Futures and Trading Commission (CFTC), the OECD, the Federal Reserve Bank of St. Louis and from the websites of Prof. Kenneth French, Prof. Nancy Xu and Prof. Jeffrey Wurgler. Appendix A provides details on the predictors.

4. Main Empirical Results

4.1. Model estimation

The hedging strategies of the representative producer are deployed sequentially in an out-of-sample (OOS) exercise deemed to mimic hedging decisions in real time. At each sample week *t,* all elements of Equation (2) such as the covariance $\sigma_{s,f,t}$, variance $\sigma_{f,t}^2$, futures return forecast, $E_t(\Delta f_{t+1}|\Omega_t)$, and corresponding hedge ratios are obtained from a L-length window of past data. The OOS return of the hedge portfolio from week *t* to *t*+1 is computed using Equation (1) and the estimation window is rolled forward by one week.

In the main analysis, we adopt weekly (Monday) rebalancing, estimation windows of L =10 years, a coefficient of relative risk aversion γ equal to 5 as in Gao and Nardari (2018), and a tracking error threshold $\varsigma = 2\%$ p.a. for the K-Integr hedge as in Barroso et al. (2022). For the VAR selective hedge, the maximum lag order is identified using the Akaike Information Criteria (AIC) as in Furió and Torró (2020) and is set to a maximum of 12.

The steps involved to calculate the RF forecasts follow Gu et al. (2020). First, we split the sample into a training sample (the initial 60% of the estimation window) and a validation sample (the most recent 40% of the estimation window). We pool the information on the K predictors and target returns into a panel for each (training and validation) sample. Second, we optimize the random forest over the training sample using predetermined values of the hyperparameters[5] and evaluate the fit of the trained random forest by calculating its mean squared forecast error (MSFE) over the validation sample. Third, the values of the hyperparameters that deliver the lowest MSFE over the validation sample are used to optimize the random forest over the entire (training and validation) estimation sample, and ultimately, to forecast the futures return using the most recent vector of predictors. Following the machine learning literature, we optimize the random forest once a year (last week of September to match with the initial week of the 10-year estimation window) and use the most recent random forest to get OOS forecasts for the weeks in between two optimizations.

4.2. Traditional and selective hedge ratios

Table 3 reports summary statistics for the traditional (MinVar) hedge ratios and for the selective (HistAve, AR, VAR, EWC, K-Integr and RF) hedge ratios. A plausible pattern is observed in the HistAve, AR, VAR, EWC and RF selective hedges – they dictate more short futures positions than the traditional hedge when the futures return is on average negative over the sample period, and

[5] The hyperparameters are the number of simulations in the random forest, B; the number of predictors in each split, R; and the maximum number of branches or depth of the tree, L. The range of values of the hyperparameters is: B=300; R= {3, 5, 10, 20, 30}; L={1, 2, ..., 6}.

less short positions than MinVar when the futures return is on average positive. To illustrate, a producer of natural gas with futures contracts exhibiting a low mean return of -33.62% p.a. (in Table 2) takes on average more short futures positions according to the HistAve selective hedge (1.14) than with the MinVar hedge (0.89). At the other extreme, a producer of unleaded gas with futures contracts exhibiting a large mean return of 29.38% p.a. (in Table 2) takes on average fewer short futures positions according to the HistAve hedge (0.78) than with the MinVar hedge (1.20). By contrast, the K-Integr hedge ratio moves close to the MinVar hedge ratio suggesting that the tracking error threshold $\varsigma = 2\%$ adopted thus far is rather strict.

[Insert Table 3 around here]

The MinVar hedge ratio is the most stable with an average standard deviation of 4% across commodities (Table 3, Panel E). The selective hedge ratios are far more volatile, especially those that hinge on RF forecasts (average standard deviation of 56%), VAR forecasts (54%) and AR forecasts (32%) with the K-Integr strategy providing the least volatile selective hedge (12%). Figure 1 illustrates this pattern for cocoa. Naturally, more volatile selective hedge ratios will be penalized by higher rebalancing costs which we examine later. We turn now to the issue of whether the larger volatility of the selective hedges reflects useful information towards greater expected utility gains or instead noise.

[Insert Figure 1 around here]

4.3. Hedging effectiveness

Table 4 presents the expected utility gain of each hedging strategy. According to Table 4, Panel E, the average expected utility gain of the MinVar hedge equals 16.27% a year, while that of the selective hedges stands at merely 13.67% across strategies. Thus, speculation decreases expected utility gains by 3.29% a year across commodities and hedging strategies. The evidence therefore recommends traditional over selective hedging. The last column of Table 4 presents the difference in expected utility gains obtained between the selective hedges and the MinVar hedge on a per-commodity basis. While speculation has a positive impact on the expected utility gains of energy commodities (unleaded gas, natural gas), it substantially decreases the expected utility gains of livestock (feeder cattle, live cattle) and metal (gold, platinum, silver, copper) commodities.

[Insert Table 4 around here]

Looking at each of the selective hedges in turn, the closest competitor to the MinVar hedge is the K-Integr hedge; its average expected utility gain at 16.61% is very close to that of MinVar (at 16.27%). Next come the expected utility gains of the HistAve, EWC and AR hedges at 15.73%, 15.72%, and 13.31%, respectively. The lowest expected utility gains of 9.22% and 7.28% correspond to the VAR and RF selective hedges; their poor performance may reflect estimation risk since the number of estimated parameters then becomes quite high (e.g., the maximum lag order of the VAR model is 11). Otherwise, the literature has shown that the effectiveness of machine learning approaches is closely aligned with the presence of ample data samples (see e.g., Gu et al. 2020). The limited number of commodities (*N*=24), predictors (*K*=37), and the relatively short sample length (beginning at best from September 1993) may explain the poor performance of the RF selective hedge.

Furthermore, we provide statistical significance for the hypothesis that the expected utility gains of MinVar are at least as high as those of selective hedging by deploying the McCracken and Valente (2018) test. As detailed in Section 2.3, the null hypothesis is $H_0\colon \Delta U_{SH_i} - \Delta U_{MinVar} \leq 0$ versus $H_1\colon \Delta U_{SH_i} - \Delta U_{MinVar} > 0$. The McCracken and Valente (2018) test p-values presented in Table 4 are generally large which indicates that the expected utility gains of the traditional MinVar strategy are at least as high as those of the selective hedges. Examining closely the commodities for which the expected utility gains of a selective hedge are seemingly superior to those of MinVar, the difference is almost always statistically insignificant according to the McCracken and Valente (2018) test. Natural gas stands out as an exception (the HistAve, AR and EWC selective hedge generate expected utility gains that are significantly higher than that of MinVar). A similar conclusion applies to live cattle under the K-Integr hedge. For all other commodities, the traditional MinVar hedge is the most effective risk management approach.

We compute the net returns of each strategy as $\Delta p_{t+1} = \Delta s_{t+1} - h_t \Delta f_{t+1} - \left| h_t - h_{t-1} e^{\Delta f_t} \right| \times TC$ using the 8.6 basis point transaction cost (TC) estimate of Marshall et al. (2012). We then calculate the net expected utility gain of each strategy using Equation (1). Table 4, Panel E presents the results. As expected, transaction costs have a noticeable impact on the expected utility gains of the most volatile selective hedges. For example, they decrease the expected utility gains of the RF, AR, and VAR hedges by 0.51%, 1.05% and 1.61% a year, respectively. The impact of transaction costs on the MinVar hedge is minimal (0.05%). Accounting for transaction costs thus reinforces our previous claim regarding the superiority of traditional hedging over selective hedging.

Our hedging analysis has thus far used front-end futures contracts. Next, we construct the hedges using instead the 2nd , 3rd, … or 6th maturity contracts along the futures curve. The results, available upon request, highlight the superiority across maturities of the MinVar and K-Integr hedges in terms of expected utility gains. They also show that the expected utility gains decrease with the maturities of the hedging instrument as implied by then-higher levels of basis risk.

To sum up, Table 4 reveals that the expected utility gains of traditional hedging are not surpassed by those of the selective hedges considered. MinVar hedging is also cheaper in terms of transaction costs and simpler to implement since it does not rely on any return forecast. Commodity hedgers should therefore focus on risk minimization solely; they shall not incorporate their market views into their hedging program. Next, we study the reasons behind the unrivalled expected utility gains of the traditional MinVar strategy.

4.4. Understanding the unrivalled effectiveness of traditional hedging

Why cannot selective hedging outperform traditional hedging in terms of expected utility gains? One explanation is that the data generating process of the commodity futures price is a pure random walk and hence, there is no predictability. Under this setting the expected futures return is $E_t(\Delta f_{t+1}|\Omega_t) = 0$ and the speculative component in Equation (2) disappears which is aligned with the absence of a risk premium at individual commodity level (Erb and Harvey, 2006). An alternative explanation is that there is time-series predictability at the commodity futures level, but the speculative profits are too small to compensate for the higher risk incurred, leading to the demise of selective hedging. To shed light on these issues we measure the accuracy of the commodity futures return predictions used in the selective hedges via: *i*) purely statistical loss functions, and *ii*) economic loss functions.

We begin by calculating the out-of-sample R-squared (R^2_{OOS}) statistic inspired from Campbell and Thompson (2008) for each of the forecasting models that underlie the selective hedges, that is,

$$R^2_{OOS} = 1 - \frac{\sum_t \left(\Delta f_{t+1} - \widehat{\Delta f}_{SH,t+1}\right)^2}{\sum_t \left(\Delta f_{t+1} - \widehat{\Delta f}_{MinVar,t+1}\right)^2} = 1 - \frac{\sum_t \left(\Delta f_{t+1} - \widehat{\Delta f}_{SH,t+1}\right)^2}{\sum_t \Delta f^2_{t+1}} \tag{5}$$

where $\widehat{\Delta f}_{SH,t+1}$ is the OOS forecast of the futures return obtained from a given selective hedging strategy.[6] Since traditional hedging rules out speculation, the relevant no predictability benchmark

[6] The K-Integr model does not provide any explicit futures returns forecast. However, assuming that $\boldsymbol{\omega}'_t \boldsymbol{z}_t \approx \frac{E_t(\Delta f_{t+1}|\Omega_t)}{\gamma\, \sigma^2_{f,t}}$, we implicitly estimate its forecast as $\widehat{\Delta f}_{K-Integr,t+1} = \gamma\, \sigma^2_{f,t}\left(\boldsymbol{\omega}'_t \boldsymbol{z}_t\right)$.

in Equation (5) is the zero forecast, $\widehat{\Delta f}_{MinVar,t+1} = 0$. We test for statistical significance by deploying the Diebold and Mariano (1995) t-test for the null hypothesis H_0: $\left(\Delta f_{t+1} - \widehat{\Delta f}_{MinVar,t+1}\right)^2 - \left(\Delta f_{t+1} - \widehat{\Delta f}_{SH,t+1}\right)^2 \leq 0$ versus H_1: $\left(\Delta f_{t+1} - \widehat{\Delta f}_{MinVar,t+1}\right)^2 - \left(\Delta f_{t+1} - \widehat{\Delta f}_{SH,t+1}\right)^2 > 0$ where $\widehat{\Delta f}_{MinVar,t+1} = 0$ by construction. Any t-statistic more than 1.65 will demonstrate a superior statistical forecast accuracy of selective hedging over traditional hedging at the 5% level.

Table 5 presents the R^2_{OOS} measures of each selective hedge and associated t-test statistics. We note that many R^2_{OOS} are negative (some of them at the 5% level), which indicates that the predictions obtained from the selective models are less reliable than the zero-return predictions assumed by MinVar. In more detail, the zero-return forecasts of the MinVar hedge beat the forecasts of the K-Integr hedge for 29% of the commodities considered; this percentage dramatically increases to 62.5% for RF, 70.8% for EWC, 79.2% for AR, 87.5% for HistAve and 100% for VAR. This result corroborates the lack of predictive superiority of selective hedging over MinVar. We note however that this general result does not extend to natural gas, unleaded gas and lean hogs that obtained positive (albeit statistically insignificant) R^2_{OOS} values from most selective hedging models.

[Insert Table 5 around here]

We now turn our attention to the economic benefit of the forecasts using the mean-variance utility as the implicit loss function. Accordingly, we zoom into the two potential sources of expected utility gain from hedging: profitability gain and risk reduction. We begin by estimating spanning regressions of the selective hedge portfolio returns on the returns of the traditional MinVar hedge portfolio (benchmark). The regression intercept or "alpha" is a measure of the economic accuracy of the predictive models as it can be interpreted as the excess or abnormal profitability of selective hedging. Table 6 presents the annualized intercept alongside Newey-West adjusted *t*-statistics. The "alpha" generation ability of the selective hedge portfolio is negligible, namely, selective hedging does not generate returns to the commodity producer beyond those from traditional MinVar hedging. Natural gas is again the exception: relaxing the zero futures return assumption accrues significant excess returns through the HistAve, AR, EWC and RF hedges.[7]

[Insert Table 6 around here]

Next, we appraise the second source of the expected utility gains from hedging: risk reduction. Specifically, we assess the ability of each of the hedges to reduce spot price risk by comparing the variance of the hedge portfolio returns. Following Wang et al. (2015), we provide statistical significance by deploying the Diebold and Mariano (1995) *t*-test for the significance of variance differential. The null hypothesis is that the variance of the selective hedge portfolio is smaller than, or equal to, that of the traditional hedge portfolio $H_0: E(\Delta p_{i,t}^2) - E(\Delta p_{MinVar,t}^2) \leq 0$ versus the alternative $H_1: E(\Delta p_{i,t}^2) - E(\Delta p_{MinVar,t}^2) > 0$, with $\Delta p_{i,t}^2$ and $\Delta p_{MinVar,t}^2$ denoting the squared returns of the selective and traditional hedge portfolios as proxies for the corresponding variances. The test statistic is $\frac{E(d_t)}{\sqrt{\widehat{var}[E(d_t)]}}$ where $d_t = \Delta p_{i,t}^2 - \Delta p_{MinVar,t}^2$ and $\widehat{var}[E(d_t)]$ is a consistent estimate of $var[E(d_t)]$. Under the assumption that d_t is stationary, the Diebold and Mariano statistic follows asymptotically the standard normal distribution under the null hypothesis.

[7] The natural gas industry has undergone significant transformations during our sample period, with perhaps the most notable being the shale gas revolution. This revolution brought about a sudden and substantial surge in natural gas supply, leading to a subsequent drop in natural gas prices. As an illustration of this shift, natural gas futures obtain a mean return of -33.62% (with a t-statistic of -3.25) in this period. These observations can explain why selective hedging models provide an accurate forecast of natural gas futures returns.

Table 7 presents the annualized variances of the hedge portfolio returns and the *p*-values of the Diebold and Mariano (1995) test. With an average variance of 3.37%, the MinVar hedge portfolio stands out as the least volatile. This is by construction of the MinVar hedge ratio which is designed to minimize the variance of the hedge portfolio without targeting performance. The selective hedge portfolios present average variances that range from 3.45% (K-Integr hedge) to 8.46% (RF hedge).[8] In statistical terms, the *p*-values of the Diebold and Mariano (1995) test present overwhelming evidence that selective hedging increases risk relative to traditional hedging. This is very damaging to selective hedging as the increase in risk that we observe is not compensated by an increase in performance or abnormal return, as just discussed. The only exception is again natural gas for which the HistAve, AR and EWC selective hedges offer positive alphas at the 5% level for risk levels that are like that of traditional hedging. The last column of Table 7 presents the difference in the variances between the selective hedge portfolios and the MinVar portfolio on a per-commodity basis. Speculation increases risk dramatically for the livestock (feeder cattle, live cattle) and metal (gold, platinum, silver, copper) commodities. Noticeably, these commodities suffer the most from speculation in terms of expected utility gains in the last column of Table 4.

[Insert Table 7 around here]

Altogether, we conclude that the inability of selective hedging to beat traditional hedging in terms of expected utility gains stems both from the lack of statistical and economic return predictability at the individual commodity futures level and from the substantial increase in risk of the selectively

[8] We additionally assessed the downside risk of the various hedge portfolios using the semi-deviation and left-tail 1% VaR measures. The results, available upon request, indicate that the traditional (MinVaR) hedge portfolio is less risky than the selective hedges also in this sense. For instance, MinVar obtains the lowest Gaussian 1% VaR of -0.0478. This ranges from -0.0875 (RF) to -0.0490 (K-Integr) for the selective hedge strategies.

hedge portfolios compared to the MinVar portfolio. All in all, commodity producers are better off if they do not engage in speculative futures trading and if they focus solely on hedging spot price risk as dictated by the no-predictability tenet.

5. Robustness Tests

This section tests whether the inability of the selective hedges to improve upon the expected utility gain of the traditional MinVar hedge is robust to various aspects of the empirical analysis. In the interest of space, we hereafter report the expected utility gains across commodities and/or across sectors with the results per commodity available upon request.

5.1. Alternative specifications of the traditional hedging strategies

The theoretical model of Anderson and Danthine (1981) motivates our choice of the OLS hedge ratio as the traditional risk-minimizing component of the selective hedge ratio. We recognize however the contribution of Wang et al. (2015) who study the OOS performance of a large range of traditional hedges and highlight the superior risk minimizing properties of the naïve one-to-one hedge ratio. Following their lead, we consider alternative traditional hedge ratios, alongside their corresponding selective hedge counterparts, such as: the naïve one-to-one hedge ratio, the vector autoregressive (VAR(1,1)) hedge ratio, the vector error correction (VEC(1,1)) hedge ratio, the bivariate DCC-GARCH(1,1) hedge ratio, the bivariate BEKK-GARCH(1,1) hedge ratio, and the regime switching-OLS hedge ratio.[9]

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[9] More specifically, the VAR(1,1) hedge ratio considers a bivariate VAR model with spot and futures returns, the VEC(1,1) hedge ratio considers a bivariate VEC model with spot and futures returns and the residual of the OLS long run regression between their log prices, the bivariate DCC-GARCH(1,1) hedge ratio and the bivariate BEKK-GARCH(1,1) hedge ratio are based on one-period ahead forecasts of the variance-covariance matrix of spot and futures returns, and the regime switching-OLS hedge ratio models the hedge ratio in high versus low volatility regimes.

Table 8 presents the expected utility gain obtained under these alternative specifications of the traditional and corresponding selective hedges as averaged across commodities. Our main evidence on the difficulty of generating through speculation higher expected utility gain than those provided by traditional hedging holds irrespective of the traditional hedge considered. For example, the average expected utility gain of traditional hedging equals 16.34% across commodities and specifications of the traditional hedge ratio; the corresponding averages for the selective hedges equal 16.67% (K-Integr), 15.61% (HistAve), 15.58% (EWC), 13.51% (AR), 9.68% (VAR) and 7.13% (RF).[10]

[Insert Table 8 around here]

5.2. Alternative specifications of the selective hedging strategies

5.2.1.EWC selective hedge

We now entertain different specifications of the selective hedging strategies, starting with the EWC hedge. Conditioning the speculative component of the selective hedge upon a smaller set of variables could improve the effectiveness of selective hedging if additional variables add more noise than signal. First, instead of the 37 predictors considered thus far, we center our attention on the set of 10 commodity-specific characteristics listed Appendix A or on the three characteristics that Barroso et al. (2022) focus on in their currency selective hedging exercise: roll-yield, momentum, and value. In the present context, trimming down the information set slightly erodes the expected utility gains of the EWC hedge as shown in the "All Comm." or "3 Commo." columns

[10] Corroborating the conclusion of Wang et al. (2015) on traditional hedging, we note that sophisticated hedge ratios (such as BEKK-GARCH) only marginally increase expected utility relative to the naïve one-to-one approach.

of Table 9, Panel A. Thus, if anything, shrinking the information set serves to underscore the superiority of the traditional hedge.

[Insert Table 9 around here]

Motivated by the literature on stock return forecasting (Rapach et al., 2010; Neely et al., 2014; Rapach and Zhou, 2022), we consider selective hedges that hinge on alternative combinations of the univariate regression forecasts. Instead of equally weighing those forecasts (as with the EWC hedge), we weigh them by the inverse of their past MSFE so that the more accurate forecasts receive higher weights. Second, we deploy the Elastic Net (E-Net) approach that blends notions from the Least Absolute Shrinkage and Selection Operator (LASSO) and ridge regressions towards a sparse forecast combination (Hollstein et al., 2021; Rapach and Zhou, 2022). Details on the combination strategies with MSFE and E-Net weighting schemes are provided in Appendix B. In Table 9, Panel A, the expected utility gains of the baseline EWC hedge are not improved by the consideration of these alternative weighting schemes, suggesting that MinVar remains unchallenged.

Following Neely et al. (2014), we extract the first (two first) principal component(s) (PC) from the full set of predictive variables over the past L observations and entertain a variant of the EWC selective hedge whose futures return forecasts derive from the predictive power of this (these) principal component(s). The expected utility gains from the resulting selective hedges, denoted PC1 and PC1-2 in Table 9, Panel A, are substantially less than those of the EWC hedge. These robustness checks therefore do not challenge our main finding on the superiority of traditional hedging.

5.2.2. K-Integr selective hedge

As in the preceding section, we begin by deploying the K-Integr hedge using a smaller subset of the original predictors that comprise either 10 or 3 commodity characteristics. Table 9, Panel B, presents averages of the expected utility gains and shows that the superiority of MinVar is not contested by either of these variants. Adding an Elastic Net (E-Net) regularization to the objective function of Equation (3) as detailed in Appendix C does not alter our conclusion either.

Our main analysis shows that the K-Integr selective hedge is the closest challenger to MinVar. This may be because the tracking error constraint $\varsigma = 2\%$ in Equation (3) is too stringent and thus, the speculative component of the K-Integr hedge is not allowed to shine. To test this hypothesis, we allow the speculative component to play a larger role by setting $\varsigma = \{5\%, 10\%\}$. The results presented in Table 9, Panel B indicate that easing the tracking error constraint decreases the average expected utility gains of the K-Integr hedge (from 16.61% when $\varsigma = 2\%$ down to 13.51% when $\varsigma = 10\%$). Therefore, our initial conclusion that K-Integr is the closest challenger to MinVar is not *because* of, but *despite,* the speculative component, which confirms that speculation hurts more than it helps in maximizing expected utility.

Inspired by Brandt et al. (2009) and Barroso et al. (2022), we also test whether one could obtain more efficient hedges by pooling together the information coming from all *N* commodities. Hopefully, the broader information set will yield more robust estimates of the K-Integr hedge ratios; it could also enable us to exploit cross-sectional predictability if at all present in the data. The hedger's problem is then to define the optimal combination, $\boldsymbol{\omega_t}$, of predictors, $\boldsymbol{z_t}$, that maximizes her expected utility; namely,

$$\max_{\omega_t} E_t\left[U\left(\Delta p_{K-Integr,t+1}\right)\middle|\Omega_t\right] = \max_{\omega_t} E_t[U(\Delta s_{t+1} - (\boldsymbol{\beta}_t - \boldsymbol{\omega}_t'\boldsymbol{z_t})\Delta f_{t+1})|\Omega_t] \quad (6)$$

$$\text{subject to } \sigma\left(\Delta p_{MinVar,t+1} - \Delta p_{K-Integr,t+1}\right) \leq \varsigma,$$

where Δs_{t+1}, Δf_{t+1}, $\Delta p_{K-Integr,t+1}$ and $\Delta p_{MinVar,t+1}$ are vectors of total returns of spot assets, futures contracts, K-Integr hedge portfolio and MinVar hedge portfolio, respectively, pooled into a panel, $\boldsymbol{\beta}_t$ is a vector of MinVar hedge ratios, $\boldsymbol{\omega}_t$ is a vector of utility maximizing weights, $\boldsymbol{z_t}$ is a matrix of standardized predictors that are also pooled into a panel, and the other parameters are as previously defined. By construction, the optimization function of Equation (6) forces the weights assigned to the predictors to be the same across commodities ($\boldsymbol{\omega}_t' = \boldsymbol{\omega}_{i,t}'$ for all $i = \{1, \dots, N\}$) which induces more robust estimates of the individual K-Integr hedge ratios. The latter are measured as follows: $h_{i,t} = \beta_{i,t} - \boldsymbol{\omega}_t' \boldsymbol{z}_{i,t}$. The expected utility gains, reported in the last column of Table 9, Panel B, indicate that one does not gain from pooling the information from the whole cross-section of commodities together. Specifically, the expected utility gain of the pooled K-Integr hedge is at 16.63% across commodities versus 16.61% for the per-commodity scenario of Table 4.[11] Taken altogether, these results reiterate that it is, in practice, difficult for commodity hedgers to benefit from speculation.

Our study focuses on the canonical problem of a producer of a single commodity (or, alternatively, a purchaser of that commodity) who, in the absence of hedging, is inherently exposed to the spot price risk of that specific commodity. However, some hedgers may have exposure to several commodities. For instance, some commodity trading firms (e.g., Trafigura) diversify their risks by trading different commodities (Pirrong, 2014). In unreported results, we consider a hypothetical cross-commodity hedger who has a long 1/N exposure in each of the N commodities present in a given sector. Yet again, the K-Integr hedge fails to outperform the MinVar hedge based on

[11] This inference is unchanged if we add the E-Net regularization to the panel Equation (6) or if we relax the tracking error constraint.

McCraken-Valente *p*-values for different in expected utility gains. The conclusion holds per sector and across commodities. We conclude therefore that irrespective of whether the hedger produces one or more commodities, speculation does not improve hedging decisions.[12]

5.2.3. RF selective hedge

Table 4 demonstrates that the RF hedge fails to provide higher expected utility gains than the MinVar hedge. The baseline RF specification allowed for the full set of 37 predictors to predict futures returns. Would expected utility gains rise if the information set was restricted to 10 or 3 commodity characteristics only? The results, presented in Table 9, Panel C, demonstrate an improvement in expected utility gains compared to the base case scenario but not to the extent that the superiority of MinVar is challenged.

As another robustness check, we test whether alternative machine learning architectures could enhance the effectiveness of selective hedging further. Following recent advances in machine learning (Fischer and Krauss, 2018; Gu et al., 2020; Chen et al., 2023; Rad et al., 2023), we design selective hedges whose futures return forecasts are based on deep neural networks (DNN) with either two hidden layers (DNN2 with 32 and 16 nodes in each respective layer) or three hidden layers (DNN3 with 32, 16 and 8 nodes). The DNN architecture is also considered in conjunction with 4 or 8 LSTM units, where the LSTM feature is here to capture potential long-run nonlinear predictability as present in the data.[13] The steps of these approaches are similar to those of the

[12] We note however that, due to diversification, the expected utility gains of the diversified producer (at 3.86% for MinVar and at 4.29% for K-Integr when across the *N* commodities) are substantially less than the average expected utility gains of the single-commodity producer (at 16.27% for MinVar in Table 4 and at 16.63% for K-Integr in Table 9, Panel B).

[13] The long-short term algorithm may be important given that some predictors (e.g., term spread) are known to anticipate well long economic trends, while others (e.g., momentum) work better as short-term predictors. The number of units follows from Chen et al. (2023) and Rad et al. (2023).

random forest detailed in Section 4.1 but using the following hyperparameters: maximum number of epochs (100), batch size (20% of the trained sample), patience of 5 evaluations, learning rate (0.001 or 0.01), Adam optimization with Huber loss function, and overfitting penalties: early stopping, dropout layer (5%), batch normalization, ensemble net (500) and *l2* regularization (10^{-5} or 10^{-3}). Table 9, Panel C, presents the results. None of the machine learning hedges provides higher expected utility gain than MinVar. In other words, machine learning fails to generate forecasts that are accurate and stable enough to challenge our main conclusion.

5.2.4. Alternative selective hedges

By Equation (1), one must take into consideration both the accuracy and the smoothness of the futures return forecasts to achieve significantly greater expected utility gains than MinVar. Following recent developments in the predictability literature, we reduce the volatility of the baseline individual forecasts by weighting them equally (Comb; Cakici et al., 2023) or by combining each of them with the HistAve forecast (Naïve Model Averaging; Chen et al., 2022). We then use the close-form solution of Equation (2) to design the selective hedging strategies called Comb and Naïve Model Averaging. The results presented in Table 9, Panel D, show that both combination approaches yield significant improvements in expected utility gains compared to the baseline selective hedges of Table 4. That is, the average increase in expected utility gain equals 3.33% for Comb and 2.96% for the Naïve Model Averaging in comparison with the baseline selective hedging models. Nevertheless, even with these improvements, the combined models fall short of surpassing the expected utility gain achieved by MinVar.

In the spirit of Fama and MacBeth (1973) cross-sectional regression (see also Lewellen, 2015), we obtain futures returns forecasts from cross-sectional (CS) predictive regressions and use them to design the so-called CS selective hedge ratios. The approach is as follows. First, we estimate each week the slopes from cross-sectional regressions of the commodity futures returns at week t on commodity-specific characteristics at week t-1.[14] The estimated cross-sectional slopes are then averaged over the 10 years preceding hedging decision and these averages are used, alongside the most recent commodity characteristics, not only to forecast commodity futures returns one week ahead, but also to estimate the time t CS selective hedge ratio. Table 9, Panel D, shows that the CS selective hedging strategy delivers a commendable expected utility gain of 14.56% a year across commodities but its performance lags that of the MinVar model.

Finally, under the assumption that the futures curve stays the same, the roll-yield today is a naïve forecast of the expected futures return (see., e.g., De Roon et al., 2003). We apply this concept to create a last selective hedging strategy called Naïve Basis, where $E_t(\Delta f_{t+1}|\Omega_t) = 7 \cdot roll - yield_t/D_t$ with $roll - yield_t = f_{1,t} - f_{2,t}$, $f_{1,t}$ and $f_{2,t}$ are the logarithmic prices of the front- and second-end futures contracts, respectively, and D_t is the number of calendar days between the two contracts at time t. The results, reported in the last column of Table 9, Panel D, show that the Naïve Basis strategy offers an average expected utility gain that ranks amongst the lowest obtained. Altogether, our comprehensive robustness analysis serves to corroborate our main conclusion on the difficulty of selective hedging to beat traditional hedging.

5.3. Are the findings sample specific?

To assess whether the superiority of the traditional MinVar hedge is an artifact of the sample period considered, we now re-evaluate hedging effectiveness over different sub-periods. First, we consider

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[14] The cross-sectional regressions only consider as independent variables the commodity specific characteristics (defined in the Appendix A) and omit the sensitivities of commodity futures returns to the macro-economic, financial and sentiment variables. Including both would lead to the number of independent variables (37) exceeding the number of dependent variables (24). We also consider a restricted model with only roll-yield, momentum and value as predictors.

the sub-periods before and after January 2006 which roughly marks the start of the financialization period (Stoll and Whaley, 2010). Second, we classify the sample weeks as those pertaining to U.S. recessions and expansions as identified by the National Bureau of Economic Research (NBER). Finally, we divide the sample weeks into those pertaining to high and low volatility periods according to the median value of two volatility measures: i) a commodity-specific volatility obtained as the weekly fitted value from a GARCH(1,1) model fitted to the spot returns series, and ii) a market-wide volatility given by the macro uncertainty index of Jurado et al. (2015).

The expected utility gains of hedging calculated over subsamples, as displayed in Table 10, corroborate the difficulty of persistently surpassing the expected utility gain of traditional hedging. As a byproduct, all hedging strategies, except RF hedge strategy, reassuringly confirm the economic intuition that commodity producers benefit the most from hedging when it is mostly needed – the expected utility gains from hedging become greater in bad times, that is, during recessions and periods of high volatility. The poor performance of RF hedge strategy in NBER recessions could be attributed to the model's annual estimation, which might not be able to detect abrupt changes in the business cycle.

[Insert Table 10 around here]

5.4. Non-constant risk aversion

Thus far, we have assumed that the commodity producer's attitude to risk is constant through time by adopting a fixed coefficient of relative risk aversion γ. However, it is well known that risk aversion rises in periods of uncertainty. Accordingly, we now allow for a time-varying coefficient of relative risk aversion, γ_t, in Equation (2), and thus, the speculative term is allowed to play a larger role in periods of lower risk aversion. The selective hedge ratio can be rewritten as $h_t =$

$\beta_t - \frac{E_t(\Delta f_{t+1}|\Omega_t)}{\gamma_t\, \sigma^2_{f,t}}$, where γ_t is the time-varying coefficient of relative risk aversion of Bekaert et al. (2022) with its full sample average at 3.0624 entering Equation (4).

[Insert Table 11 around here]

Table 11, Panel A reports the expected utility gains obtained for the various hedges and corroborates the difficulty of outperforming the traditional MinVar hedge. On average across commodities, the expected utility gain of MinVar is 9.41% which is similar to that of the *K*-Integr hedge (9.83%). The expected utility gains of HistAve, EWC and RF are inferior at 8.58%, 8.54% and 6.01%, respectively. Finally, the negative expected utility gain of VAR at -1.71% suggests that relative to deploying the risky VAR hedge, producers are better off not hedging at all.

5.5. Estimation window and rebalancing frequency

The hedging strategies have been thus far deployed sequentially using rolling estimation windows of length $L = 10 \times 52$ weeks and weekly rebalancing. We now use expanding windows starting at L = 520 observations. As the length of the estimation windows increases, the parametric forecasts of futures returns (i.e., those from AR, VAR, EWC, K-Integr and RF) can improve or worsen depending on two effects – longer windows reduce estimation risk or sampling uncertainty but the risk of conflating different economic regimes increases which introduces forecast biases. The expected utility gains from expanding windows, presented in Table 11, Panel B, are very similar to those from the rolling window analysis and thus, the superiority of the traditional MinVar hedge is not challenged.

The baseline analysis assumes that the strategies are rebalanced weekly. This frequency strikes us as a reasonable middle-of-the-ground approach given that the literature on commodity hedging uses either daily (Baillie and Myers, 1991), weekly (Cotter and Hanly, 2012, 2020; Wang et al.,

2015) or monthly (Cotter and Hanly, 2012, 2020; Furio and Torro, 2020) hedging frequencies. Acknowledging that hedging frequencies vary across companies,[15] we test the robustness of our conclusions to the rebalancing frequency of the hedge by considering monthly (month-end settlement prices) and quarterly (quarter-end settlement prices) rebalancing. A further rationale for entertaining these lower frequencies reflects upon the observation that return predictability rises with the forecasting horizon (Gargano and Timmermann, 2014), and thus, lower rebalancing could potentially improve the expected utility gains of selective hedging. The results, reported in Table 11, Panels C and D, show that, lower rebalancing improves hedging effectiveness by 3.36% (5.70%) on average for monthly (quarterly) rebalancing. However, the main conclusion of the difficulty of outperforming the expected utility gain of the MinVar model holds irrespective of the rebalancing frequency considered.

5.6. Long hedging

Thus far, the analysis has assumed that the agent is a commodity producer who contemplates a short hedge. We now address the hedging problem of a processor or a consumer of the physical commodity who contemplates a long hedge. The change in the value of the hedge portfolio is given by $\Delta p_{t+1} = -\Delta s_{t+1} + h_t \Delta f_{t+1}$ and the selective hedge ratio that solves Equation (2) is $h_t = \beta_t + \frac{E_t(\Delta f_{t+1}|\Omega_t)}{\gamma\, \sigma_{f,t}^2}$ with $\beta_t = \frac{\sigma_{s,f,t}}{\sigma_{f,t}^2}$ denoting as before the traditional MinVar hedge ratio.

[15] Bodnar et al. (1998) sheds light on this heterogeneity. Surveying 399 non-financial firms, they revealed that 28% chose to revalue their derivatives portfolios daily or weekly, 27% monthly, 21% quarterly and 5% annually. The remaining companies declare reevaluating their hedging strategy as per needed. These results indicate a shift from the more frequent rebalancing practices observed in their 1995 survey.

Table 11, Panel E presents the expected utility gain of the long hedges. Over the sample period under study, short hedging (Table 4) generates an average expected utility gain that is 4.45% higher than the average expected utility gain obtained via long hedging. However, this average masks large commodity heterogeneity. For example, for natural gas the expected utility gains of short hedging exceed those of long hedging by 53.47%, while for unleaded gasoline the expected utility gains of long hedging are 26.69% larger than those of short hedging. More importantly for the present purpose, traditional long hedging provides expected utility gains at least as high as those achieved through selective long hedging.

6. Conclusions

This article performs a comparative analysis of traditional and selective hedging strategies in commodity futures markets. The traditional hedger solely seeks to minimize risk and therefore assumes that commodity futures prices follow a pure random walk. The selective hedger maximizes her expected utility by simultaneously minimizing risk and speculating on the change in the futures price over the hedging horizon. In turn, the predictive models that we use to generate expectations of futures returns range from naïve as proxied by the historical average return, to more sophisticated as enabled by recent developments in forecast combination, style integration, and machine learning.

Deploying the hedging strategies weekly in an out-of-sample exercise for 24 commodities, we find that traditional hedging provides expected utility gains that are at least as high as those obtained with selective hedging. Our comprehensive study of hedging methods across commodity products shows that it is very challenging in practice for selective hedging to improve upon the expected utility gain of traditional hedging because the increase in risk incurred by speculation is not compensated by higher performance. This situation is heightened by bringing transaction costs into consideration as the selective hedges are more trading intensive. These findings hold after accounting for numerous specifications of the traditional and selective hedging strategies, various subsamples, time-varying risk aversion, longer estimation windows, monthly and quarterly rebalancing, as well as long versus short hedging.

The main takeaway of our paper is therefore that hedgers shall exert caution while incorporating their market views into their hedging program. This conclusion echoes the lessons learned from various speculation-led hedging fiascos and corroborates the at-best small increases in firm value obtained through selective hedging (Adam and Fernando, 2006; Brown et al., 2006). While our comparative studies make use of state-of-the-art forecasting models, we cannot rule out the possibility that further advances in time-series predictability at the asset level or the incorporation into the hedging decision of private information could rescue selective hedging. We welcome developments in these directions.

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Appendix A. **Commodity futures return predictors.**

10 commodity futures characteristics:

- *Roll-yield*: Logarithmic price differential between the front- and second-nearest contracts, $f_{1,t} - f_{2,t}$.
- *Momentum*: Front-end excess returns as averaged over the preceding year, $\frac{1}{52}\sum_{j=0}^{51} \Delta f_{1,t-j}$.
- *Value*: Logarithm of the average *D* daily front-end futures prices 4.5 to 5.5 years before portfolio formation *t* minus the current front-end futures price, $\frac{1}{D}\sum_{d=0}^{D-1}(f_{1,t-d} - f_{1,t})$.
- *Average hedging pressure*: Weekly net short open positions of futures commercials (or hedgers) over their total open positions as an average over the prior year, $\frac{1}{52}\sum_{j=0}^{51} \frac{Hedg_{t-j}^{short} - Hedg_{t-j}^{long}}{Hedg_{t-j}^{short} + Hedg_{t-j}^{long}}$. The Commitment of Traders (CoT) report from the Commodity Futures Trading Commission (CFTC) discloses short and long open positions. These positions reflect holdings by large hedgers in commodity futures, with positive (negative) values indicating that the hedgers are net short (long) on average for a specific commodity. This data is gathered on Tuesdays and published on Fridays.
- *Net position change of hedgers:* Weekly change in the net long position of hedgers, normalized by open interest, $\frac{Hedg_{t}^{net\ long} - Hedg_{t-1}^{net\ long}}{OI_{t-1}}$.
- *Basis-momentum*: difference in the average returns between the front- and second-nearest contracts on the prior year, $\frac{1}{52}\sum_{j=0}^{51} \Delta f_{1,t-j} - \frac{1}{52}\sum_{j=0}^{51} \Delta f_{2,t-j}$.
- *Skewness*: Third moment of the *D* daily front-end excess returns within the past year, $\frac{1}{D}\frac{\sum_{d=0}^{D-1}(\Delta f_{1,t-d} - \mu_t)^3}{\sigma_t^3}$.
- *Relative basis*: Difference in front- and second-nearest roll-yields, $(f_{1,t} - f_{2,t}) - (f_{2,t} - f_{3,t})$.
- *Illiquidity*: Absolute excess return of the front-end futures contract per weekly dollar volume as averaged over the *W* weeks within the past two months, $\frac{1}{W}\sum_{j=0}^{W-1} \frac{|\Delta f_{1,t-j}|}{\$Volume_{t-j}}$.
- *Change in open interest:* Change in the average open interest along the futures curve.

27 financial, macroeconomic and sentiment indicators:

- Term spread: Yield difference between 10-year Treasury bonds and 3-month Treasury bills.
- Default spread: Yield difference between Moody's seasoned Baa and Aaa corporate bonds.
- TED spread: Difference between 3-month U.S. LIBOR rate and 3-month U.S. Treasury bill rate.
- 3-month T-bill.
- Long-term US bond returns.
- US market excess return.

- Dividend yield.[*]
- Earning price ratio.[*]
- (Log changes) Industrial production.[*,**]
- (Log changes) Money supply.[*,**]
- Unemployment rate.[*,**]
- Inflation rate.[*,**]
- FX rates (US dollar versus AU dollar, CA dollar, NZ dollar, SA rand, Indian rupee).
- Chicago FED national activity index.[*,**]
- (Log changes) Economic policy uncertainty index.
- (Log changes) Geopolitical risk index.
- (Log changes) Baltic dry index: Weighted average freight price (Bakshi et al., 2012).
- (Changes) Real economic activity index of Kilian (2009). [*,**]
- Business confidence index.[*,**]
- Consumer confidence index[*,**]
- Sentiment index of Baker and Wurgler (2006). [*]
- Uncertainty index of Bekaert et al. (2022).
- VIX.

[*] indicates monthly series that have been fixed for all the weeks within the month.

[**] indicate series that have been lagged two months to control for publication lags.

Appendix B: Alternative specifications of the EWC selective hedge

The EWC hedge ratio is based on expectations of futures returns derived from the combination of univariate forecasts from K predictors; $E_t(\Delta f_{t+1}|\Omega_t) = \boldsymbol{\omega}_t' \Delta\hat{\boldsymbol{f}}_{t+1}$ with $\Delta\hat{f}_{k,t+1} = \hat{\alpha}_0 + \hat{\alpha}_1 z_{k,t}$, $k = 1, \dots, K$, and $\boldsymbol{\omega}_t' = \left(\frac{1}{K}, \dots, \frac{1}{K}\right)$. We now entertain alternative weighting schemes.

MSFE weighting scheme

The MSFE weighting scheme depends on forecast accuracy, with higher weights assigned to the forecasts with lower MSFE. The weights are calculated as follows. Each week *t*, the window of $L = 10 \times 52$ weeks is divided into an estimation window and an evaluation window of equal length ($L_0 = L_1 = \frac{L}{2}$). The first L_0 weeks are used to generate the *K* out-of-sample univariate forecasts of futures returns, $\Delta\hat{f}_{k,t+1}$, for the first week of the evaluation period. The estimation window is then expanded by one week and a second set of *K* forecasts is generated for the second week of the evaluation period, and so forth. The MSFE is calculated over the L_1 period as $MSFE_{k,t} = \sum_{j=0}^{L_1-1}(\Delta f_{t-j+1} - \Delta\hat{f}_{t-j+1})^2/L_1$. The weighting scheme used at observation *t* to generate $E_t(\Delta f_{t+1}|\Omega_t)$ is then $\omega_{k,t} = \frac{MSFE_{k,t}^{-1}}{\sum_{k=1}^{K} MSFE_{k,t}^{-1}}$. This procedure is repeated at the next rebalancing time *t*+1.

E-Net weighting scheme

The E-Net weighting scheme reduces the complexity of the predictive model by adding the elastic net penalty terms to the loss function of the forecast combination. The E-Net weights are obtained as follows: on each week *t*, we divide the window of $L = 10 \times 52$ preceding weeks into an estimation window and an evaluation window of equal length ($L_0 = L_1 = \frac{L}{2}$). We solve the following minimization problem over the holdout period

$$\sum_{j=0}^{L_1-1}\left(\Delta f_{t-j+1} - \sum_{k=1}^{K}\beta_k \Delta\hat{f}_{k,t-j+1}\right)^2 + \lambda\left(0.5(1-\delta)\sum_{k=1}^{K}|\beta_k| + \delta\sum_{k=1}^{K}\beta_k^2\right)$$

$\Delta\hat{f}_{k,t-j+1}, k = 1, \dots, K$, are the univariate forecasts obtained over the evaluation period, and λ and δ are the LASSO and ridge regularization parameters, respectively. We set $\delta = 0.5$ and select λ using the adjusted AIC of Hurvich and Tsai (1989). The E-Net weighting scheme used at observation *t* to generate $E_t(\Delta f_{t+1}|\Omega_t)$ is then $\omega_{k,t} = \frac{I(\beta_k > 0)}{\sum_{k=1}^{K} I(\beta_k > 0)}$, with $I(\cdot)$ an indicator variable. The selective E-Net hedge is thus based on what can be interpreted as a sparse combination of *K* univariate regression forecasts.

Appendix C: K-Integr selective hedge with E-Net penalty

The K-Integr objective function with an Elastic Net (E-Net) regularization combines a LASSO penalty and a Ridge penalty for overfitting. The maximization problem of the hedger then becomes

$$\max_{\omega_t} E_t\left[U\left(\Delta p_{K-Integr,t+1}\right)\middle|\Omega_t\right]$$

$$= \max_{\omega_t} E_t\left[U(\Delta s_{t+1} - (\beta_t - \boldsymbol{\omega}_t' \boldsymbol{z_t})\Delta f_{t+1}) + \lambda_1 \textstyle\sum_{k=1}^{K}\left|\omega_{k,t}\right| + \lambda_2 \sum_{k=1}^{K} \omega_{k,t}^2 \left|\Omega_t\right.\right] \qquad \text{(C1)}$$

$$\text{subject to } \sigma\left(\Delta p_{MinVar,t+1} - \Delta p_{K-Integr,t+1}\right) \leq \varsigma,$$

where $U(\cdot)$ is the mean-variance utility function, Δs_{t+1}, Δf_{t+1}, $\Delta p_{K-Integr,t+1}$ and $\Delta p_{MinVar,t+1}$ are spot, futures, K-Integr and MinVar returns for commodity *i* at time *t*+1, respectively, β_t is the MinVar hedge ratio of commodity *i* at time *t*, $\boldsymbol{\omega}_t$ is a time *t* vector of weights specific to commodity *i*, $\boldsymbol{z_t}$ is *K*-vector of predictors for commodity *i* and λ_1 and λ_2 are LASSO and Ridge penalty parameters, respectively, that are set to the same value, λ, to speed up the computation time.

The K-integr with E-Net regularization each week follows a 4-step process. First, the estimation window of $L = 10 \times 52$ weeks is divided into an initial optimization sample (60%) and the remaining evaluation sample (40%). Second, setting λ to a specific value, we use the optimization sample to optimize the weights $\boldsymbol{\omega}_{i,t}$ (Equation C1) and the evaluation sample to measure the expected utility gain of the optimized portfolio (Equation 4). Third, Step 2 is repeated for a large range of values of λ. The optimal value of λ that is chosen is the one that maximizes the utility of the optimized portfolio over the evaluation sample. Finally, the optimized value of λ selected in Step 3 is used to optimize the weights, $\boldsymbol{\omega}_{i,t}$, in Equation (C1) over the entire (optimization and evaluation) sample.

Figure 1. Evolution of traditional and selective hedge ratios for a cocoa producer

This figure plots the traditional MinVar hedge ratio (in black) and six alternative selective hedge ratios (in grey) for a representative cocoa producer with assumed mean-variance utility function and coefficient of relative risk aversion $\gamma = 5$. The rebalancing frequency is weekly.

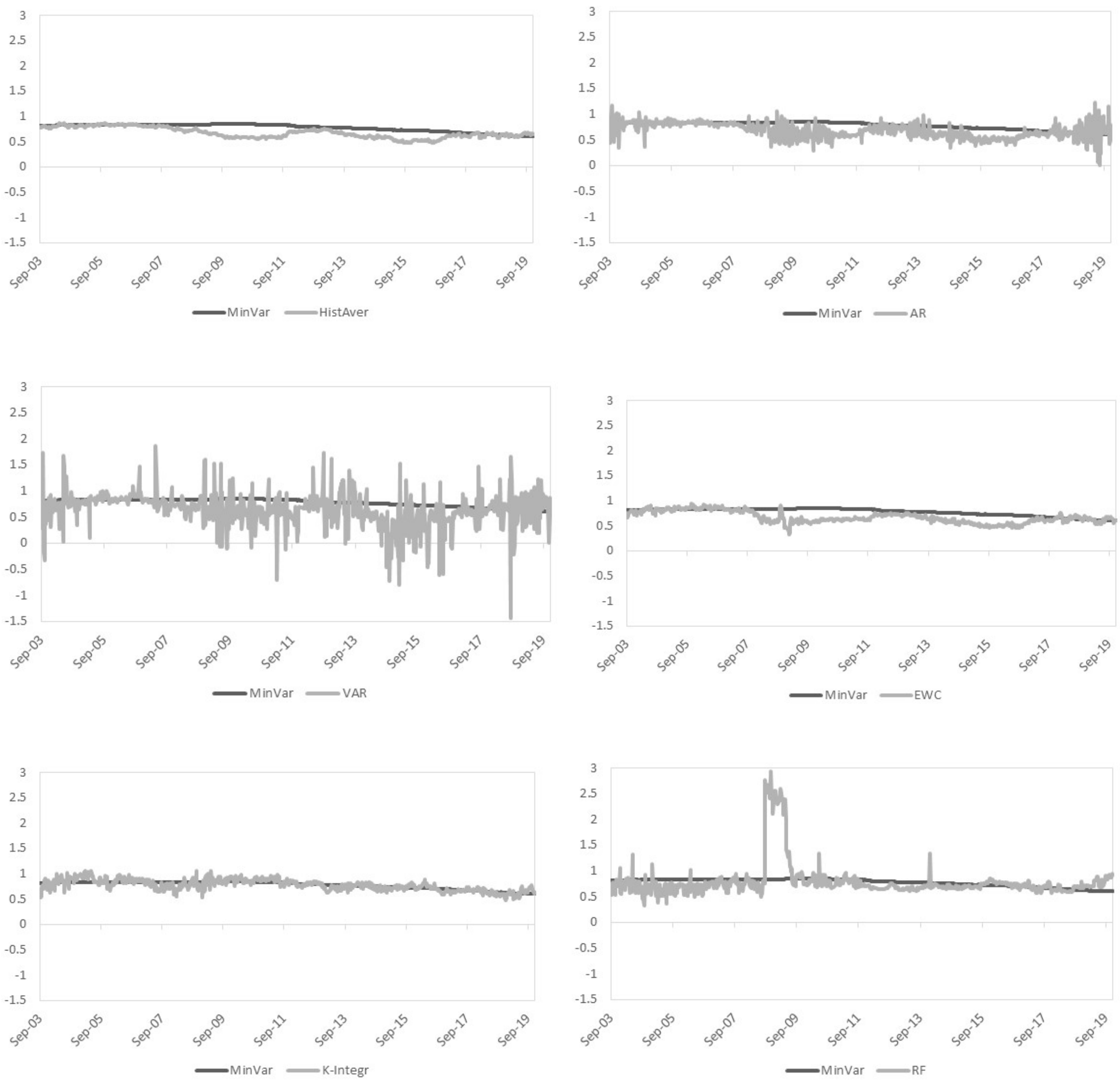

Table 1. Selective hedging strategies

Selective hedge ratio	Strategy	Name	References
$h = argmax\ U = \beta - E_t(\Delta f_{t+1}\vert\Omega_t)/\gamma\sigma_f^2$ $E_t(\Delta f_{t+1}\vert\Omega_t) = \frac{1}{L}\sum_{j=0}^{L-1}\Delta f_{t-j}$	Selective hedge based on recent historical average of futures returns	HistAve	
$h = argmax\ U = \beta - E_t(\Delta f_{t+1}\vert\Omega_t)/\gamma\sigma_f^2$ $E_t(\Delta f_{t+1}\vert\Omega_t) = \hat{\alpha}_0 + \hat{\alpha}_1\Delta f_t$	Selective hedge based on AR model forecast	AR(1)	Cotter and Hanley (2010), Cotter and Hanley (2012)
$h = argmax\ U = \beta - E_t(\Delta f_{t+1}\vert\Omega_t)/\gamma\sigma_f^2$ $E_t(\Delta f_{t+1}\vert\Omega_t) = \hat{\theta}_0 + \hat{\theta}_1\Delta f_t + \cdots + \hat{\theta}_p\Delta f_{t-p}$ $+\hat{\varphi}_1 roll\_y_t + \cdots + \hat{\varphi}_p roll\_y_{t-p}$ $roll\_y_t = f_{1,t} - f_{2,t}$	Selective hedge based on VAR(p) model forecast	VAR(p)	Furio and Torro (2020)
$h = argmax\ U = \beta - E_t(\Delta f_{t+1}\vert\Omega_t)/\gamma\sigma_f^2$ $E_t(\Delta f_{t+1}\vert\Omega_t) = \boldsymbol{\omega}_t'\widehat{\boldsymbol{\Delta f}}_{t+1}, \boldsymbol{\omega}_t' = \left(\frac{1}{K}, \dots, \frac{1}{K}\right)$ with $\Delta f_{k,t+1} = \hat{\alpha}_0 + \hat{\alpha}_1 z_{k,t}$	Selective hedge based on equally-weighted forecast combination	EWC	
$max_\omega\ U(\beta, \boldsymbol{\omega})$ s.t. MinVar tracking error $h = \beta - \boldsymbol{\omega z}$	Selective hedge based on optimized integration of predictors	K-integr	Barroso et al. (2022)
$h = argmax\ U = \beta - E_t(\Delta f_{t+1}\vert\Omega_t)/\gamma\sigma_f^2$ $E_t(\Delta f_{t+1}\vert\Omega_t) = g^*(\boldsymbol{z_t})$	Selective hedge based on random forest forecasts	RF	

Note: β is the traditional MinVar hedge ratio that minimizes the variance of the hedge portfolio.

Table 2. Descriptive statistics of spot and futures returns

The table presents summary statistics for the total returns of spot and front-end fully-collateralized futures positions, as well as the spot-futures returns correlations. Mean and variance are annualized. Newey-West robust t-statistics for the significance of the mean are in parentheses and p-values for the significance of the correlation are in curly brackets. The last columns report the out-of-sample sample period.

	Spot				Futures				Correlation		Sample period	
	Mean		Variance	Utility	Mean		Variance	Utility			Start	End
Panel A: Agriculture												
Cocoa	0.0190	(0.33)	0.0688	-0.1531	0.0383	(0.61)	0.0854	-0.1753	0.82	{0.00}	29/09/2003	23/12/2019
Coffee	0.0551	(0.88)	0.0642	-0.1053	-0.0354	(-0.49)	0.0967	-0.2771	0.69	{0.00}	29/09/2003	23/12/2019
Corn	0.0322	(0.44)	0.0904	-0.1938	-0.0516	(-0.71)	0.0828	-0.2586	0.93	{0.00}	29/09/2003	23/12/2019
Cotton	0.0065	(0.09)	0.0859	-0.2083	-0.0107	(-0.15)	0.0825	-0.2170	0.94	{0.00}	29/09/2003	23/12/2019
Frozen orange juice	0.0179	(0.23)	0.1192	-0.2801	-0.0082	(-0.11)	0.1135	-0.2919	0.97	{0.00}	29/09/2003	23/12/2019
Soybeans	0.0234	(0.34)	0.0719	-0.1562	0.0704	(1.16)	0.0598	-0.0791	0.95	{0.00}	29/09/2003	23/12/2019
Soybeans meal	0.0206	(0.25)	0.1137	-0.2635	0.1206	(1.69)	0.0792	-0.0773	0.90	{0.00}	29/09/2003	23/12/2019
Soybeans oil	0.0186	(0.31)	0.0650	-0.1439	-0.0106	(-0.19)	0.0590	-0.1582	0.97	{0.00}	29/09/2003	23/12/2019
Sugar	0.0437	(0.57)	0.0954	-0.1948	-0.0430	(-0.55)	0.0947	-0.2798	0.91	{0.00}	29/09/2003	23/12/2019
Wheat	0.0369	(0.40)	0.1416	-0.3172	-0.0961	(-1.27)	0.0974	-0.3397	0.83	{0.00}	29/09/2003	23/12/2019
Panel B: Energy												
Crude oil	0.0495	(0.55)	0.1403	-0.3013	-0.0284	(-0.32)	0.1145	-0.3146	0.94	{0.00}	29/09/2003	23/12/2019
Gasoline RBOB	-0.1390	(-0.73)	0.0846	-0.3504	-0.0332	(-0.21)	0.0478	-0.1528	0.82	{0.00}	03/10/2011	02/03/2015
Heating oil	0.0651	(0.81)	0.1096	-0.2088	0.0270	(0.34)	0.0937	-0.2074	0.95	{0.00}	29/09/2003	23/12/2019
Natural gas	-0.0431	(-0.34)	0.4698	-1.2176	-0.3362	(-3.25)	0.1806	-0.7876	0.60	{0.00}	29/09/2003	23/12/2019
Unleaded gas	0.2041	(0.82)	0.2038	-0.3053	0.2938	(1.38)	0.1342	-0.0417	0.89	{0.00}	29/09/2003	04/12/2006
Panel C: Livestock												
Feeder cattle	0.0660	(1.14)	0.0398	-0.0336	0.0568	(1.20)	0.0239	-0.0030	0.41	{0.00}	29/09/2003	06/07/2015
Lean hogs	0.0197	(0.19)	0.0724	-0.1612	-0.0666	(-0.89)	0.0579	-0.2114	0.30	{0.00}	29/09/2003	06/07/2015
Live cattle	0.0191	(0.45)	0.0314	-0.0594	0.0152	(0.40)	0.0267	-0.0514	0.53	{0.00}	29/09/2003	23/12/2019
Panel D: Metal and Lumber												
Copper	0.0752	(1.02)	0.0685	-0.0961	0.0919	(1.25)	0.0701	-0.0834	0.98	{0.00}	29/09/2003	23/12/2019
Gold	0.0825	(2.05)	0.0306	0.0061	0.0758	(1.89)	0.0307	-0.0009	0.99	{0.00}	29/09/2003	23/12/2019
Lumber	-0.0048	(-0.06)	0.0973	-0.2482	-0.1083	(-1.41)	0.1010	-0.3609	0.36	{0.00}	29/09/2003	12/08/2019
Palladium	0.1322	(1.72)	0.0951	-0.1055	0.1267	(1.64)	0.0965	-0.1146	0.96	{0.00}	29/09/2003	23/12/2019
Platinum	0.0173	(0.29)	0.0509	-0.1099	0.0202	(0.34)	0.0524	-0.1109	0.96	{0.00}	29/09/2003	23/12/2019
Silver	0.0736	(0.98)	0.0983	-0.1723	0.0636	(0.84)	0.0981	-0.1817	0.98	{0.00}	29/09/2003	23/12/2019

Table 3. Summary statistics for traditional and selective hedge ratios

The table reports the mean and standard deviation (StDev) of the traditional MinVar hedge ratio and selective hedge ratios using HistAve, AR, VAR, EWC, K-Integr and RF predictions. The hedges are implemented weekly out-of-sample over the specific sample periods detailed in Table 2.

	MinVar hedge ratios		Selective hedge ratios													
			HistAve		AR		VAR		EWC		K-Integr		RF	
	Mean	StDev	Mean	StDev	Mean	StDev	Mean	StDev	Mean	StDev	Mean	StDev	Mean	StDev
Panel A: Agriculture														
Cocoa	0.77	0.07	0.68	0.10	0.68	0.15	0.64	0.33	0.67	0.12	0.78	0.11	0.80	0.37
Coffee	0.62	0.08	0.70	0.13	0.71	0.26	0.75	0.51	0.69	0.14	0.64	0.10	0.66	0.36
Corn	0.96	0.02	1.12	0.13	1.13	0.38	1.18	0.47	1.12	0.17	0.97	0.10	1.05	0.54
Cotton	0.94	0.04	1.05	0.17	1.04	0.22	0.98	0.40	1.04	0.20	0.95	0.09	1.00	0.47
Frozen orange juice	0.98	0.02	1.00	0.10	1.00	0.32	0.95	0.61	1.01	0.16	0.97	0.09	1.03	0.49
Soybeans	1.02	0.02	0.73	0.09	0.74	0.30	0.72	0.55	0.73	0.14	1.02	0.11	1.11	0.62
Soybeans meal	1.06	0.02	0.66	0.08	0.66	0.27	0.67	0.61	0.67	0.12	1.06	0.10	1.13	0.51
Soybeans oil	1.02	0.01	1.03	0.18	1.04	0.23	1.02	0.45	1.04	0.22	1.04	0.10	1.07	0.55
Sugar	0.85	0.04	0.81	0.16	0.81	0.24	0.77	0.31	0.82	0.18	0.86	0.11	0.89	0.38
Wheat	1.02	0.02	1.25	0.12	1.26	0.26	1.29	0.39	1.25	0.14	1.03	0.08	1.11	0.49
Panel B: Energy														
Crude oil	1.02	0.06	0.94	0.29	0.93	0.37	1.00	0.43	0.96	0.29	1.02	0.08	1.04	0.30
Gasoline RBOB	1.03	0.00	0.87	0.04	0.88	0.18	0.77	0.85	0.84	0.09	1.13	0.28	0.93	0.04
Heating oil	1.05	0.04	0.94	0.16	0.94	0.27	0.93	0.36	0.95	0.17	1.04	0.09	1.08	0.31
Natural gas	0.89	0.07	1.14	0.25	1.15	0.26	1.13	0.43	1.14	0.24	0.88	0.10	0.91	0.19
Unleaded gas	1.20	0.02	0.78	0.04	0.79	0.32	0.76	0.39	0.76	0.05	1.17	0.06	1.10	0.10
Panel C: Livestock														
Feeder cattle	0.56	0.07	-0.02	0.15	-0.01	0.92	-0.13	0.98	0.00	0.25	0.58	0.23	0.76	2.06
Lean hogs	0.36	0.06	0.51	0.08	0.51	0.20	0.52	0.43	0.53	0.12	0.35	0.14	0.41	0.62
Live cattle	0.54	0.03	0.28	0.32	0.29	0.77	0.39	1.19	0.29	0.34	0.56	0.19	0.72	1.42
Panel D: Metal and Lumber														
Copper	0.98	0.01	0.72	0.21	0.74	0.27	0.74	0.51	0.73	0.28	0.98	0.09	1.08	0.57
Gold	0.98	0.01	0.49	0.27	0.49	0.37	0.60	0.97	0.48	0.31	0.98	0.16	1.08	1.27
Lumber	0.36	0.06	0.63	0.13	0.64	0.16	0.60	0.26	0.62	0.17	0.35	0.11	0.40	0.38
Palladium	0.95	0.02	0.83	0.12	0.82	0.18	0.83	0.38	0.82	0.16	0.93	0.11	0.96	0.27
Platinum	0.92	0.04	0.59	0.38	0.60	0.54	0.58	0.63	0.62	0.41	0.89	0.17	0.98	0.64
Silver	0.98	0.01	0.82	0.11	0.82	0.21	0.83	0.47	0.83	0.16	0.98	0.10	1.04	0.48
Panel E: All commodities	0.88	0.04	0.77	0.16	0.78	0.32	0.77	0.54	0.78	0.19	0.88	0.12	0.93	0.56

Table 4. Expected utility gain

The table reports the expected utility gains achieved by the traditional MinVar and selective hedging strategies derived with HistAve, AR, VAR, EWC, K-Integr and RF forecasts. Positive numbers indicate that hedging the spot position provides greater expected utility to the hedger than not hedging (c.f. Table 2). The numbers in parentheses are bootstrap p-values for the McCracken and Valente (2018) statistic with null hypothesis $H_0\colon \Delta Udiff_i = \Delta U_i - \Delta U_{MinVar} \leq 0$ and alternative hypothesis $H_1\colon \Delta Udiff_i = \Delta U_i - \Delta U_{MinVar} > 0$, where ΔU is the expected utility gain as defined in Equation (4) and i stands for the selective hedging strategy at hand. The average utility gains across commodities are summarized in Panel E before and after transaction costs (TC). The sample periods are as detailed in Table 2.

	MinVar	Selective hedging (SH)												SH -
		HistAver		AR		VAR		EWC		K-Integr		RF		MinVar
Panel A: Agriculture														
Cocoa	0.0836	0.0745	(0.88)	0.0668	(0.90)	0.0447	(0.86)	0.0662	(0.97)	0.0848	(0.63)	0.0454	(0.88)	-0.0199
Coffee	0.0936	0.0752	(0.96)	0.0341	(0.98)	0.0139	(0.82)	0.0781	(0.89)	0.1000	(0.26)	0.0588	(0.89)	-0.0336
Corn	0.2473	0.2261	(0.96)	0.1871	(0.98)	0.1682	(0.92)	0.2204	(0.97)	0.2495	(0.39)	0.2059	(0.82)	-0.0377
Cotton	0.1955	0.1784	(0.95)	0.1452	(1.00)	0.0782	(0.97)	0.1768	(0.94)	0.1981	(0.37)	0.1378	(0.89)	-0.0430
Frozen orange juice	0.2881	0.2704	(0.97)	0.2299	(1.00)	0.1369	(0.99)	0.2655	(0.99)	0.2816	(0.76)	0.2395	(0.89)	-0.0508
Soybeans	0.0893	0.0840	(0.63)	0.0507	(0.94)	0.0165	(0.90)	0.0783	(0.74)	0.0948	(0.28)	-0.0109	(0.86)	-0.0370
Soybeans meal	0.1012	0.0956	(0.56)	0.0121	(0.99)	-0.0492	(0.94)	0.0930	(0.61)	0.1082	(0.24)	0.0031	(0.86)	-0.0574
Soybeans oil	0.1658	0.1541	(0.88)	0.1387	(0.89)	0.1374	(0.79)	0.1462	(0.94)	0.1695	(0.34)	0.0736	(0.88)	-0.0292
Sugar	0.2372	0.2260	(0.87)	0.2070	(0.95)	0.1919	(0.97)	0.2260	(0.83)	0.2472	(0.18)	0.1911	(0.88)	-0.0223
Wheat	0.3426	0.3204	(0.93)	0.2929	(0.97)	0.2646	(0.99)	0.3219	(0.90)	0.3382	(0.69)	0.2604	(0.93)	-0.0428
Panel B: Energy														
Crude oil	0.3468	0.3197	(0.95)	0.2966	(0.94)	0.1988	(0.94)	0.3464	(0.46)	0.3509	(0.31)	0.3333	(0.78)	-0.0392
Gasoline RBOB	0.1766	0.1647	(0.67)	0.2438	(0.52)	0.2211	(0.59)	0.1603	(0.74)	0.1855	(0.99)	0.1758	(0.45)	0.0153
Heating oil	0.2132	0.2085	(0.58)	0.1895	(0.85)	0.1549	(0.91)	0.2172	(0.38)	0.2166	(0.40)	0.1841	(0.84)	-0.0180
Natural gas	0.7132	0.7743	(0.05)	0.7559	(0.17)	0.6564	(0.81)	0.7749	(0.04)	0.7224	(0.20)	0.7269	(0.30)	0.0219
Unleaded gas	0.0445	0.1197	(0.13)	0.1129	(0.19)	0.0026	(0.69)	0.1201	(0.14)	0.0459	(0.46)	0.0977	(0.09)	0.0387
Panel C: Livestock														
Feeder cattle	-0.0129	-0.0178	(0.48)	-0.0810	(0.96)	-0.0953	(0.94)	-0.0159	(0.45)	-0.0078	(0.32)	-0.3550	(0.92)	-0.0826
Lean hogs	0.0415	0.0443	(0.36)	0.0575	(0.32)	0.0504	(0.46)	0.0437	(0.39)	0.0516	(0.18)	0.0400	(0.71)	0.0064
Live cattle	0.0137	-0.0091	(0.99)	-0.0762	(1.00)	-0.0711	(0.95)	-0.0131	(1.00)	0.0237	(0.14)	-0.0891	(0.85)	-0.0529
Panel D: Metal and Lumber														
Copper	0.0740	0.0599	(0.76)	0.0386	(0.85)	-0.0173	(0.88)	0.0738	(0.41)	0.0763	(0.46)	-0.0971	(0.89)	-0.0517
Gold	0.0002	-0.0033	(0.48)	-0.0219	(0.80)	-0.0665	(0.86)	-0.0149	(0.79)	-0.0075	(0.81)	-0.5253	(0.93)	-0.1068
Lumber	0.0752	0.0631	(0.80)	0.0527	(0.93)	0.0662	(0.62)	0.0586	(0.89)	0.0840	(0.13)	0.0629	(0.80)	-0.0106
Palladium	0.0961	0.1058	(0.27)	0.1127	(0.31)	0.0483	(0.75)	0.1096	(0.24)	0.1034	(0.88)	0.0480	(0.89)	-0.0081
Platinum	0.1029	0.0783	(0.94)	0.0373	(0.98)	-0.0044	(0.96)	0.0842	(0.85)	0.0958	(0.74)	-0.0451	(0.89)	-0.0618
Silver	0.1752	0.1614	(0.94)	0.1122	(0.99)	0.0643	(0.99)	0.1556	(0.97)	0.1734	(0.55)	-0.0148	(0.93)	-0.0665
Panel E: All commodities														
Before TC	0.1627	0.1573		0.1331		0.0922		0.1572		0.1661		0.0728		-0.0329
After TC	0.1622	0.1564		0.1227		0.0760		0.1553		0.1629		0.0677		-0.0387

Table 5. Statistical forecast accuracy

The table reports the out-of-sample predictive accuracy OOS-R^2 for the futures return forecast that underlies each selective hedge relative to the no-predictability or zero risk premium assumption that underlies the traditional (MinVar) hedge. Significance Diebold and Mariano (1995) *t*-statistics are reported in parentheses. Positive and statistically significant OOS-R^2 statistics suggest that the mean square error associated with the forecast at hand is lower than that associated with the zero futures return assumption.

	HistAver		AR		VAR		EWC		K-Integr		RF	
Panel A: Agriculture												
Cocoa	-0.32%	(-1.69)	-0.52%	(-2.09)	-1.32%	(-2.63)	-0.46%	(-2.07)	0.05%	(0.34)	-0.87%	(-0.82)
Coffee	-0.34%	(-1.90)	-1.14%	(-2.29)	-1.66%	(-1.94)	-0.25%	(-1.32)	0.16%	(1.21)	-0.69%	(-0.99)
Corn	-0.31%	(-1.27)	-0.72%	(-1.22)	-0.93%	(-1.24)	-0.38%	(-1.33)	-0.01%	(-0.10)	0.72%	(0.68)
Cotton	-0.45%	(-1.51)	-0.85%	(-2.18)	-2.07%	(-3.33)	-0.46%	(-1.22)	0.03%	(0.19)	-0.53%	(-0.49)
Frozen orange juice	-0.32%	(-2.42)	-0.66%	(-1.34)	-1.76%	(-2.00)	-0.35%	(-1.88)	-0.09%	(-0.87)	-0.23%	(-0.40)
Soybeans	-0.06%	(-0.17)	-0.35%	(-0.63)	-0.97%	(-1.21)	-0.13%	(-0.32)	0.13%	(1.03)	-0.35%	(-0.23)
Soybeans meal	0.06%	(0.10)	-0.73%	(-0.88)	-2.13%	(-2.04)	0.08%	(0.13)	0.17%	(1.19)	-0.89%	(-0.69)
Soybeans oil	-0.24%	(-1.36)	-0.48%	(-1.59)	-0.36%	(-0.67)	-0.32%	(-1.43)	0.08%	(0.65)	0.11%	(0.08)
Sugar	-0.23%	(-1.04)	-0.54%	(-1.34)	-0.81%	(-1.64)	-0.24%	(-1.04)	0.20%	(1.28)	-0.70%	(-0.97)
Wheat	-0.20%	(-0.71)	-0.66%	(-1.38)	-1.22%	(-1.86)	-0.17%	(-0.57)	-0.04%	(-0.32)	-0.50%	(-0.59)
Panel B: Energy												
Crude oil	-0.30%	(-0.59)	-0.76%	(-1.03)	-2.52%	(-2.32)	0.08%	(0.17)	0.07%	(0.51)	0.70%	(0.59)
Gasoline RBOB	-0.53%	(-0.56)	2.61%	(1.62)	-1.22%	(-0.30)	-0.88%	(-0.79)	-1.04%	(-0.54)	0.09%	(0.11)
Heating oil	-0.29%	(-0.56)	-0.56%	(-0.73)	-1.26%	(-1.44)	0.04%	(0.09)	0.12%	(0.85)	0.71%	(0.59)
Natural gas	0.45%	(0.83)	0.08%	(0.12)	-1.95%	(-1.64)	0.63%	(1.09)	0.09%	(0.65)	0.62%	(1.25)
Unleaded gas	0.88%	(0.60)	0.50%	(0.27)	-0.93%	(-0.44)	0.92%	(0.60)	0.02%	(0.07)	0.70%	(1.52)
Panel C: Livestock												
Feeder cattle	-0.19%	(-0.37)	-0.49%	(-0.42)	-1.02%	(-0.83)	-0.15%	(-0.28)	0.11%	(0.64)	-2.37%	(-1.17)
Lean hogs	0.00%	(-0.00)	0.21%	(0.45)	-0.47%	(-0.79)	0.05%	(0.12)	0.24%	(0.93)	0.50%	(0.51)
Live cattle	-0.36%	(-1.21)	-0.98%	(-1.25)	-0.76%	(-1.00)	-0.35%	(-1.08)	0.24%	(1.87)	-0.76%	(-0.69)
Panel D: Metal												
Copper	-0.32%	(-0.59)	-0.68%	(-1.15)	-0.69%	(-0.92)	-0.10%	(-0.17)	0.08%	(0.64)	-0.20%	(-0.10)
Gold	-0.12%	(-0.22)	-0.39%	(-0.64)	-1.42%	(-2.07)	-0.28%	(-0.50)	-0.21%	(-1.65)	-3.53%	(-1.74)
Lumber	-0.16%	(-0.35)	-0.37%	(-0.76)	-0.09%	(-0.17)	-0.17%	(-0.36)	0.16%	(1.22)	0.31%	(0.49)
Palladium	0.00%	(-0.02)	0.08%	(0.26)	-1.58%	(-2.23)	0.06%	(0.17)	0.20%	(0.87)	-1.03%	(-1.34)
Platinum	-0.23%	(-0.33)	-0.79%	(-0.83)	-1.81%	(-1.80)	-0.16%	(-0.26)	-0.13%	(-0.58)	-1.04%	(-0.62)
Silver	-0.27%	(-0.75)	-0.82%	(-1.69)	-1.30%	(-1.89)	-0.36%	(-0.95)	-0.06%	(-0.46)	-1.09%	(-1.22)
Panel E: All commodities	-0.16%		-0.38%		-1.26%		-0.14%		0.02%		-0.43%	

Table 6. Economic forecast accuracy: Abnormal performance of the selective hedges

The table reports the annualized intercept or "alpha" from spanning regressions of the selective hedge portfolio returns on the returns of the traditional MinVar hedge portfolio (benchmark) with significance Newey-West *t*-statistics in parentheses. Positive and statistically significant alphas suggest that the selective hedging strategy accrues abnormal profits to the hedger versus the traditional hedging strategy. The sample periods are as detailed in Table 2.

	HistAve		AR		VAR		EWC		K-Integr		RF	
Panel A: Agriculture												
Cocoa	-0.0108	(-1.34)	-0.0173	(-1.57)	-0.0292	(-1.37)	-0.0160	(-1.71)	0.0028	(0.48)	0.0044	(0.11)
Coffee	-0.0127	(-1.59)	-0.0374	(-1.63)	-0.0164	(-0.40)	-0.0092	(-1.00)	0.0079	(1.33)	0.0001	(0.00)
Corn	-0.0110	(-0.69)	-0.0107	(-0.26)	-0.0040	(-0.08)	-0.0119	(-0.67)	0.0051	(0.68)	0.1068	(1.45)
Cotton	-0.0110	(-0.68)	-0.0294	(-1.35)	-0.0710	(-2.23)	-0.0086	(-0.42)	0.0050	(0.55)	0.0252	(0.43)
Frozen orange juice	-0.0145	(-1.63)	-0.0108	(-0.32)	-0.0158	(-0.28)	-0.0139	(-1.05)	-0.0044	(-0.70)	0.0297	(0.68)
Soybeans	0.0134	(0.78)	0.0144	(0.54)	0.0226	(0.61)	0.0124	(0.64)	0.0067	(1.04)	0.0470	(0.68)
Soybeans meal	0.0377	(1.26)	0.0080	(0.19)	-0.0021	(-0.04)	0.0394	(1.25)	0.0081	(1.07)	0.0003	(0.01)
Soybeans oil	-0.0090	(-1.07)	-0.0193	(-1.25)	0.0006	(0.02)	-0.0123	(-1.08)	0.0053	(0.88)	0.0700	(1.04)
Sugar	-0.0070	(-0.65)	-0.0159	(-0.79)	-0.0212	(-0.86)	-0.0060	(-0.54)	0.0122	(1.65)	0.0058	(0.18)
Wheat	-0.0062	(-0.35)	-0.0186	(-0.62)	-0.0237	(-0.60)	-0.0023	(-0.12)	-0.0022	(-0.29)	0.0251	(0.42)
Panel B: Energy												
Crude oil	-0.0065	(-0.25)	-0.0080	(-0.22)	-0.0557	(-1.26)	0.0224	(0.90)	0.0058	(0.85)	0.0963	(1.42)
Gasoline RBOB	-0.0062	(-0.31)	0.0749	(1.90)	0.1744	(1.43)	-0.0092	(-0.38)	0.0073	(0.23)	0.0029	(0.16)
Heating oil	0.0074	(0.36)	0.0104	(0.33)	-0.0083	(-0.21)	0.0182	(0.95)	0.0049	(0.75)	0.0524	(1.03)
Natural gas	0.0715	(2.56)	0.0610	(2.02)	0.0165	(0.38)	0.0769	(2.75)	0.0069	(1.17)	0.0418	(1.88)
Unleaded gas	0.0939	(1.07)	0.0934	(0.89)	0.0313	(0.26)	0.1013	(1.11)	0.0022	(0.16)	0.0446	(1.62)
Panel C: Livestock												
Feeder cattle	0.0121	(0.42)	0.0358	(0.55)	0.0216	(0.31)	0.0147	(0.50)	0.0084	(0.84)	0.0941	(0.85)
Lean hogs	0.0074	(0.49)	0.0271	(1.27)	0.0345	(1.36)	0.0134	(0.66)	0.0128	(1.24)	0.0926	(1.73)
Live cattle	-0.0085	(-0.54)	-0.0212	(-0.50)	0.0276	(0.65)	-0.0081	(-0.46)	0.0140	(1.98)	0.0959	(1.29)
Panel D: Metal												
Copper	0.0100	(0.36)	-0.0045	(-0.15)	0.0194	(0.40)	0.0263	(0.87)	0.0037	(0.62)	0.0535	(0.49)
Gold	0.0259	(1.03)	0.0195	(0.66)	0.0061	(0.17)	0.0200	(0.74)	-0.0055	(-0.86)	-0.0350	(-0.40)
Lumber	0.0165	(0.70)	0.0094	(0.38)	0.0270	(0.94)	0.0162	(0.67)	0.0106	(1.54)	0.0522	(1.31)
Palladium	0.0147	(1.14)	0.0246	(1.55)	-0.0090	(-0.32)	0.0224	(1.44)	0.0100	(1.13)	-0.0106	(-0.43)
Platinum	0.0192	(0.58)	0.0096	(0.22)	-0.0229	(-0.50)	0.0236	(0.73)	-0.0025	(-0.23)	0.0239	(0.31)
Silver	0.0007	(0.04)	-0.0336	(-1.16)	-0.0312	(-0.75)	-0.0021	(-0.10)	0.0004	(0.05)	-0.0144	(-0.27)
Panel E: All commodities	0.0095		0.0067		0.0030		0.0128		0.0052		0.0377	

Table 7. Economic forecast accuracy: Variance of the hedge portfolio returns

The table reports the annualized variance of the traditional MinVar and selective hedge portfolios. The Diebold and Mariano (1995) test p-values for the null hypothesis H_0: $\sigma_{i,t}^2 - \sigma_{MinVar,t}^2 \leq 0$ vs. the alternative H_A: $\sigma_{i,t}^2 - \sigma_{MinVar,t}^2 > 0$ where *i* is the selective hedge are shown in parenthesis. The sample periods are as detailed in Table 2.

	MinVar	Selective hedges (SH)												SH-MinVar
		HistAver		AR		VAR		EWC		K-Integr		RF		
Panel A: Agriculture														
Cocoa	0.0230	0.0225	(0.84)	0.0230	(0.45)	0.0273	(0.00)	0.0236	(0.16)	0.0236	(0.00)	0.0402	(0.01)	0.0037
Coffee	0.0344	0.0375	(0.00)	0.0443	(0.00)	0.0605	(0.00)	0.0377	(0.00)	0.0351	(0.02)	0.0490	(0.02)	0.0097
Corn	0.0116	0.0150	(0.00)	0.0300	(0.00)	0.0427	(0.00)	0.0169	(0.00)	0.0120	(0.04)	0.0699	(0.03)	0.0195
Cotton	0.0106	0.0125	(0.00)	0.0188	(0.05)	0.0289	(0.00)	0.0140	(0.01)	0.0115	(0.05)	0.0424	(0.01)	0.0108
Frozen orange juice	0.0068	0.0077	(0.00)	0.0253	(0.01)	0.0591	(0.00)	0.0098	(0.00)	0.0075	(0.00)	0.0371	(0.01)	0.0176
Soybeans	0.0076	0.0139	(0.00)	0.0245	(0.00)	0.0445	(0.00)	0.0154	(0.00)	0.0083	(0.00)	0.0725	(0.02)	0.0222
Soybeans meal	0.0221	0.0378	(0.00)	0.0560	(0.02)	0.0811	(0.00)	0.0393	(0.00)	0.0227	(0.03)	0.0663	(0.02)	0.0285
Soybeans oil	0.0032	0.0049	(0.00)	0.0067	(0.00)	0.0157	(0.00)	0.0069	(0.00)	0.0039	(0.00)	0.0665	(0.03)	0.0142
Sugar	0.0166	0.0183	(0.00)	0.0233	(0.00)	0.0276	(0.00)	0.0187	(0.00)	0.0176	(0.00)	0.0371	(0.03)	0.0072
Wheat	0.0442	0.0518	(0.00)	0.0570	(0.00)	0.0655	(0.00)	0.0524	(0.00)	0.0452	(0.04)	0.0839	(0.00)	0.0151
Panel B: Energy														
Crude oil	0.0167	0.0300	(0.00)	0.0367	(0.00)	0.0495	(0.00)	0.0270	(0.00)	0.0168	(0.35)	0.0482	(0.02)	0.0180
Gasoline RBOB	0.0281	0.0298	(0.01)	0.0311	(0.02)	0.0785	(0.09)	0.0304	(0.02)	0.0292	(0.22)	0.0292	(0.05)	0.0100
Heating oil	0.0110	0.0143	(0.00)	0.0230	(0.00)	0.0293	(0.00)	0.0158	(0.00)	0.0115	(0.00)	0.0457	(0.01)	0.0123
Natural gas	0.3031	0.3052	(0.41)	0.3085	(0.31)	0.3314	(0.00)	0.3075	(0.30)	0.3019	(0.85)	0.3146	(0.01)	0.0084
Unleaded gas	0.0438	0.0582	(0.01)	0.0645	(0.00)	0.0795	(0.00)	0.0609	(0.00)	0.0443	(0.26)	0.0430	(0.68)	0.0146
Panel C: Livestock														
Feeder cattle	0.0337	0.0400	(0.00)	0.0746	(0.00)	0.0747	(0.00)	0.0404	(0.00)	0.0350	(0.04)	0.2095	(0.01)	0.0453
Lean hogs	0.0661	0.0679	(0.03)	0.0706	(0.00)	0.0762	(0.00)	0.0706	(0.00)	0.0672	(0.06)	0.1043	(0.02)	0.0100
Live cattle	0.0228	0.0286	(0.00)	0.0501	(0.02)	0.0674	(0.00)	0.0305	(0.00)	0.0244	(0.00)	0.1023	(0.01)	0.0278
Panel D: Metal														
Copper	0.0024	0.0119	(0.00)	0.0147	(0.00)	0.0478	(0.02)	0.0142	(0.00)	0.0030	(0.00)	0.0935	(0.01)	0.0284
Gold	0.0009	0.0130	(0.00)	0.0177	(0.00)	0.0309	(0.00)	0.0151	(0.00)	0.0017	(0.00)	0.1958	(0.03)	0.0448
Lumber	0.0854	0.0970	(0.00)	0.0984	(0.00)	0.0999	(0.00)	0.0988	(0.00)	0.0861	(0.07)	0.1113	(0.02)	0.0132
Palladium	0.0076	0.0096	(0.00)	0.0108	(0.00)	0.0232	(0.00)	0.0109	(0.00)	0.0086	(0.01)	0.0225	(0.02)	0.0066
Platinum	0.0039	0.0218	(0.00)	0.0344	(0.00)	0.0380	(0.00)	0.0211	(0.00)	0.0058	(0.00)	0.0725	(0.03)	0.0284
Silver	0.0032	0.0088	(0.00)	0.0152	(0.00)	0.0347	(0.00)	0.0097	(0.00)	0.0039	(0.00)	0.0719	(0.02)	0.0209
Panel E: All commodities	0.0337	0.0399		0.0483		0.0631		0.0412		0.0345		0.0846		0.0182

Table 8. Alternative specifications of the traditional hedge ratios

The table reports the expected utility gains of hedging strategies that use the OLS hedge ratio (base case), the one-to-one hedge ratio, the VAR(1,1) hedge ratio, the VEC hedge ratio, the bivariate BEKK-GARCH(1,1) hedge ratio, the DCC-GARCH(1,1) hedge ratio or the regime switching-OLS hedge ratio to model the risk-minimizing component of the hedge. The reported statistics are averages across commodities. The specific sample periods are as detailed in Table 2.

	Traditional	Selective hedges					
	hedge	HistAver	AR	VAR	EWC	K-Integr	RF
OLS	0.1627	0.1573	0.1331	0.0922	0.1572	0.1661	0.0728
One-to-One	0.1597	0.1485	0.1249	0.0845	0.1481	0.1628	0.0626
VAR(1,1)	0.1628	0.1576	0.1335	0.0944	0.1575	0.1662	0.0725
VEC(1,1)	0.1627	0.1576	0.1335	0.0944	0.1575	0.1661	0.0724
BEKK-GARCH(1,1)	0.1710	0.1654	0.1503	0.1176	0.1646	0.1744	0.0769
DCC-GARCH(1,1)	0.1701	0.1584	0.1433	0.1048	0.1580	0.1730	0.0775
Regime Switching-OLS	0.1541	0.1488	0.1248	0.0854	0.1490	0.1575	0.0660
Average	0.1633	0.1562	0.1348	0.0962	0.1560	0.1666	0.0715

Table 9. Alternative specifications of the selective hedge ratios

The table reports the expected utility gains obtained from alternative specifications of the EWC (Panel A), K-Integr (Panel B), RF (Panel C) and miscellaneous (Panel D) hedging strategies. The first two columns of Panels A to C pertain to the base case setting of Table 4. 'All', 'All Comm.', and '3 Comm.' refer to the full set of 37 predictors, the 10 commodity-specific predictors, and 3 commodity predictors (roll-yield, momentum and value), respectively. In Panel A, MSFE and E-Net combine the predictions from univariate regressions using either the inverse of the mean squared forecast errors or elastic net weights as detailed in Appendix B. PC1 (PC1-2) use the first (two first) principal component(s) of the information variables as predictors. In Panel B, K-Integr E-net includes a parameter overfitting penalty based on Lasso and Ridge regularizations as detailed in Appendix C. Pooled K-Integr stacks together all the commodities and predictors in a panel before optimizing the weights. In Panel C, DNN stands for deep neural network with the number of hidden layers mentioned thereafter, LSTM stands for long-short term memory network with the number of LSTM units mentioned thereafter. In Panel D, Comb combines the predictions of all the six selective hedging models (Cakici et al., 2023), Naïve model averaging combines the HistAve predictions and those obtained from either one of the remaining five forecasting models (Chen et al., 2022), CS relies on Fama-MacBeth cross sectional forecasts (Lewellen, 2015). Naïve Basis uses the roll-yield at time *t* as futures return forecast. The expected utility gains are averaged per commodity sector and overall. The specific sample periods are detailed in Table 2.

Panel A. EWC and its variants

	MinVar	EWC			MSFE	E-Net	PC1	PC1-2
Predictors		**All**	**All Comm.**	**3 Comm.**	**All**	**All**	**All**	**All**
Agriculture	0.1844	0.1672	0.1665	0.1599	0.1672	0.1339	0.1361	0.1098
Energy	0.2988	0.3238	0.3165	0.2995	0.3218	0.3258	0.2100	0.1905
Livestock	0.0141	0.0049	0.0002	-0.0010	0.0048	-0.0334	-0.0229	-0.0576
Metal	0.0873	0.0778	0.0722	0.0564	0.0778	0.0533	0.0066	0.0011
All commodities	0.1627	0.1572	0.1534	0.1430	0.1568	0.1328	0.0993	0.0785

Panel B. K-Integr and its variants

	MinVar	K-Integr						
		Applied to single commodities						Pooled
Predictors		**All**	**All Comm.**	**3 Commo.**	**All**	**All**	**All**	**All**
Tracking error		**2%**	**2%**	**2%**	**2%**	**5%**	**10%**	**2%**
Weighting scheme		**EW**	**EW**	**EW**	**E-Net**	**EW**	**EW**	**-**
Agriculture	0.1844	0.1872	0.1806	0.1816	0.1866	0.1841	0.1595	0.1870
Energy	0.2988	0.3042	0.2968	0.2918	0.3020	0.3138	0.2784	0.3037
Livestock	0.0141	0.0225	0.0127	0.0218	0.0183	0.0238	-0.0038	0.0159
Metal	0.0873	0.0876	0.0873	0.0845	0.0857	0.0789	0.0400	0.0925
All commodities	0.1627	0.1661	0.1608	0.1608	0.1643	0.1658	0.1351	0.1663

Table 9. ***Continued***

Panel C. RF and its variants

	MinVar	RF			DNN		LSTM-DNN			
		All	All Comm.	3 Comm.	DNN2	DNN3	LSTM4-DNN2	LSTM4-DNN3	LSTM8-DNN2	LSTM8-DNN3
Agriculture	0.1844	0.1205	0.1809	0.1734	0.0949	0.1316	0.1710	0.1321	0.1782	0.1486
Energy	0.2988	0.3036	0.3082	0.2827	0.2443	0.2980	0.2896	0.3044	0.2969	0.3124
Livestock	0.0141	-0.1347	0.0114	-0.0501	-0.2033	-0.0979	-0.0181	-0.1020	0.0161	-0.0713
Metal	0.0873	-0.0952	0.0476	0.0557	-0.1677	-0.0032	0.0573	0.0200	0.0507	0.0582
All commodities	0.1627	0.0728	0.1529	0.1388	0.0231	0.1039	0.1436	0.1107	0.1508	0.1326

Panel D. Miscellaneous models

	MinVar	Comb	Naïve model averaging					CS		Naive basis
			AR	VAR	EWC	K-Integ	RF	All Comm.	3 Comm.	
Agriculture	0.1844	0.1734	0.1582	0.1507	0.1694	0.1816	0.1734	0.1580	0.1604	0.0648
Energy	0.2988	0.3258	0.3224	0.2999	0.3222	0.3182	0.3298	0.2875	0.2949	0.2225
Livestock	0.0141	0.0234	-0.0010	0.0012	0.0060	0.0183	0.0029	-0.0244	0.0080	-0.3627
Metal	0.0873	0.0797	0.0690	0.0593	0.0789	0.0885	0.0532	0.0432	0.0654	0.0740
All commodities	0.1627	0.1630	0.1502	0.1403	0.1582	0.1664	0.1546	0.1335	0.1456	0.0465

Table 10. Subsample analysis

The table reports the expected utility gains of the various hedging strategies over different subsample periods such as pre and post the financialization of commodities using the January 2006 date suggested by Stoll and Whaley (2010), during NBER expansions and recessions, and during periods of high versus low commodity market volatility (defined according to a GARCH model fitted to weekly spot returns), and high versus low macroeconomic uncertainty using the Jurado et al. (2015) index with the full sample average as the high/low threshold. The expected utility gains reported are averages across commodities per sector and overall. The sample periods are as detailed in Table 2.

	MinVar	Selective hedges						MinVar	Selective hedges					
		HistAve	AR	VAR	EWC	K-integr	RF		HistAve	AR	VAR	EWC	K-integr	RF
	Pre-financialization period							Post-financialization period						
Agriculture	0.2183	0.1998	0.1201	0.1308	0.1903	0.2230	0.2624	0.1791	0.1659	0.1393	0.0956	0.1636	0.1815	0.0977
Energy	0.0548	0.1205	0.1505	0.0797	0.1162	0.0558	0.0853	0.3921	0.3863	0.3542	0.2965	0.3952	0.3961	0.3836
Livestock	-0.0662	-0.0301	-0.1924	-0.1388	-0.0410	-0.0444	-0.0775	0.0683	0.0506	0.0346	0.0204	0.0510	0.0733	-0.1500
Metal and Lumber	-0.0508	-0.0312	-0.0151	-0.0760	-0.0299	-0.0500	-0.0384	0.1096	0.0951	0.0667	0.0299	0.0953	0.1098	-0.1044
All commodities	0.0825	0.0958	0.0494	0.0328	0.0898	0.0878	0.1088	0.1922	0.1797	0.1528	0.1116	0.1807	0.1948	0.0758
	NBER expansions							NBER recessions						
Agriculture	0.1585	0.1430	0.1102	0.0865	0.1420	0.1608	0.1587	0.4250	0.4255	0.3803	0.2286	0.4015	0.4320	-0.2333
Energy	0.2580	0.2874	0.2925	0.2301	0.2851	0.2609	0.2668	1.0532	0.8962	0.8329	0.5963	1.0420	1.0974	0.9909
Livestock	-0.0028	-0.0031	-0.0423	-0.0422	-0.0071	0.0034	-0.0152	0.1333	0.0624	0.0281	-0.0159	0.0865	0.1634	-0.9356
Metal and Lumber	0.0468	0.0476	0.0388	0.0055	0.0482	0.0496	0.0312	0.4611	0.3537	0.2078	0.1055	0.3513	0.4381	-1.2688
All commodities	0.1311	0.1310	0.1113	0.0801	0.1297	0.1342	0.1276	0.4808	0.4206	0.3469	0.2118	0.4322	0.4878	-0.4446
	Low spot volatility							High spot volatility						
Agriculture	0.1019	0.0896	0.0821	0.0661	0.0914	0.1035	0.0937	0.2673	0.2517	0.1912	0.1350	0.2435	0.2712	0.1477
Energy	0.1121	0.1626	0.1787	0.1276	0.1641	0.1119	0.1418	0.4843	0.4709	0.4596	0.3639	0.4823	0.4952	0.4646
Livestock	0.0353	0.0273	0.0058	0.0025	0.0277	0.0403	-0.0467	-0.0066	-0.0153	-0.0721	-0.0797	-0.0176	0.0050	-0.2230
Metal and Lumber	0.0181	0.0317	0.0288	0.0002	0.0335	0.0208	0.0041	0.1566	0.1235	0.0819	0.0302	0.1223	0.1546	-0.1945
All commodities	0.0748	0.0826	0.0794	0.0545	0.0841	0.0767	0.0638	0.2506	0.2320	0.1869	0.1296	0.2303	0.2554	0.0818
	Low macro uncertainty index							High macro uncertainty index						
Agriculture	0.1994	0.1911	0.1490	0.1276	0.1886	0.2067	0.2099	0.1740	0.1560	0.1277	0.0812	0.1522	0.1735	0.0575
Energy	-0.0636	0.0212	0.0408	-0.0525	0.0261	-0.0527	-0.0475	0.6317	0.6138	0.6813	0.5914	0.6217	0.6459	0.6188
Livestock	-0.0160	-0.0318	-0.1144	-0.1113	-0.0361	-0.0066	-0.0295	0.0308	0.0269	0.0132	-0.0004	0.0284	0.0388	-0.1919
Metal and Lumber	0.0603	0.0370	0.0367	0.0181	0.0399	0.0630	0.0510	0.1065	0.1066	0.0687	0.0133	0.1049	0.1051	-0.1987
All commodities	0.0829	0.0893	0.0655	0.0328	0.0895	0.0901	0.0866	0.2346	0.2229	0.2140	0.1603	0.2227	0.2380	0.0792

Table 11. Rebalancing frequency, estimation window, time-varying risk aversion and long hedging

The table presents the expected utility gains of various hedging strategies obtained when allowing for time-variation in the hedger's risk aversion (Panel A), from expanding windows (Panel B), with monthly or quarterly rebalancing (Panels C and D, respectively), and for a long hedger (Panel E). The expected utility gains reported are averages across commodities per sector and overall. The specific sample periods are as detailed in Table 2.

	MinVar	Selective hedge					
		HistAver	AR	VAR	EWC	K-Integr	RF
Panel A: Time-varying risk aversion							
Agriculture	0.1131	0.0872	0.0309	-0.0198	0.0853	0.1167	0.1008
Energy	0.1815	0.2106	0.2176	0.1038	0.2126	0.1868	0.1990
Livestock	0.0073	-0.0050	-0.0779	-0.0873	-0.0072	0.0173	-0.0172
Metal	0.0328	0.0250	-0.0059	-0.0781	0.0258	0.0342	-0.0850
All commodities	0.0941	0.0858	0.0470	-0.0171	0.0854	0.0983	0.0601
Panel B: Expanding windows							
Agriculture	0.1846	0.1795	0.1509	0.1323	0.1761	0.1860	0.1076
Energy	0.3213	0.3431	0.3224	0.2683	0.3420	0.3216	0.2929
Livestock	0.0139	0.0120	-0.0503	-0.0318	0.0063	0.0238	-0.1925
Metal	0.0880	0.0860	0.0652	0.0432	0.0860	0.0893	-0.1389
All commodities	0.1609	0.1617	0.1321	0.1113	0.1593	0.1632	0.0471
Panel C: Monthly rebalancing							
Agriculture	0.2030	0.1878	0.1800	0.1542	0.1825	0.1922	0.1334
Energy	0.3978	0.4056	0.4062	0.3417	0.4128	0.3954	0.3485
Livestock	0.0588	0.0452	0.0147	-0.1419	0.0399	0.0375	0.0062
Metal	0.1277	0.1105	0.0766	0.0169	0.1060	0.0947	-0.0785
All commodities	0.1984	0.1869	0.1708	0.1124	0.1840	0.1819	0.1093
Panel D: Quarterly rebalancing							
Agriculture	0.2068	0.2100	0.2095	0.2021	0.2082	0.1977	0.2134
Energy	0.4124	0.3975	0.3991	0.3988	0.4014	0.4152	0.4129
Livestock	0.2076	0.2353	0.2260	0.0337	0.2361	0.1818	-0.0853
Metal	0.0696	0.0614	0.0617	0.0586	0.0609	0.0641	0.0686
All commodities	0.1975	0.1985	0.1973	0.1668	0.1982	0.1887	0.1604
Panel E: Long hedging							
Agriculture	0.1288	0.1159	0.0851	0.0435	0.1127	0.1313	0.0532
Energy	0.2519	0.2509	0.2460	0.1794	0.2572	0.2535	0.2464
Livestock	-0.0490	-0.0595	-0.1045	-0.1147	-0.0582	-0.0395	-0.1807
Metal	0.0685	0.0627	0.0408	-0.0008	0.0609	0.0685	-0.1176
All commodities	0.1164	0.1081	0.0829	0.0404	0.1080	0.1192	0.0215