Does Speculation in Futures Markets Improve Commodity Hedging Decisions?

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Abstract

This paper presents a comprehensive analysis of traditional versus selective hedging strategies in commodity futures markets. Traditional hedging aims solely to reduce spot price risk, while selective hedging also seeks to enhance returns by predicting movements in commodity futures prices. We construct selective hedges using a range of forecasting techniques, from simple historical averages to advanced machine learning models, and evaluate their performance based on the expected mean-variance utility of hedge portfolio returns. Out-of-sample results for 24 commodities do not favor selective hedging over traditional hedging, as the former increases risk without delivering additional returns. These findings are robust across various hedge reformulations, expanding estimation windows, and rebalancing frequencies.

Keywords: Traditional hedging; Selective hedging; Expected utility; Commodity futures markets.
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1. Introduction

Although irrelevant in Modigliani-Miller frictionless capital markets, risk management is known to increase shareholder value in the presence of market imperfections because it can lower the cost of financial distress (Smith and Stulz, 1985; Stulz, 1996), increase the debt tax shield (Leland, 1998), or reduce expected tax payments and agency costs (Smith and Stulz, 1985). Risk management is commonly implemented in practice (Rawls and Smithson, 1990; Géczy et al., 1997) as it is perceived to reduce cash flow variation, facilitate investment in growth opportunities, or increase sales and managerial ownership, inter alia. This article performs a comparative analysis of *traditional* and *selective* hedging strategies in commodity futures markets. The objective is to test empirically whether commodity firms are likely to achieve greater utility from traditional minimum-variance hedging that solely aims at covering spot price risk or from selective hedging with an additional speculative element that is constructed upon their market views.

Selective hedging is endorsed theoretically as the equilibrium solution of rational expectations models of hedging (Anderson and Danthine, 1981, 1983; Stulz, 1984). It appears consistent with the risk management practices of commodity producers. 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 predictions about the direction of the market. Likewise, Cheng and Xiong (2014) observe that the short futures positions of corn, cotton, soybeans and wheat producers move in sync with their futures prices, suggesting again some speculative trading based on current market conditions. Surveying the risk management practices of 6,896 firms across 47 countries, Bartram (2019) observes that corporations engage in speculation within their commodity derivatives trading programs, which aligns with the notion that forecasting commodity price movements constitutes a competitive advantage to commodity firms' risk management.

Against this background, there is a dearth of empirical research on the relative merits of selective versus traditional hedging in practice. This article aims to fill in this gap. To do so, we compare the traditional minimum-variance hedging strategy that solely targets risk minimization and hence, assumes no futures price movement over the hedging horizon, and a wide spectrum of selective hedges that rely on diverse techniques to predict the futures return. We start by deploying a simple selective hedge where the futures return prediction is the historical average return. Next, we explore selective hedges that utilize futures return forecasts derived from autoregressive models (Cotter and Hanly, 2010, 2012), vector autoregressive models (Furió and Torró, 2020), combinations of univariate regression forecasts (Rapach et al., 2010), and style integration approaches similar to those developed by Brandt et al. (2009) and Barroso et al. (2022). Finally, we implement selective hedges based on cutting-edge machine learning (ML) forecasts to capture potential nonlinear relationships between commodity futures returns and a range of predictors (Fischer and Krauss, 2018; Gu et al., 2020; Chen et al., 2023). To our best knowledge, selective hedges constructed from historical average returns, univariate regression forecast combinations, and ML-based forecasts represent novel contributions to the commodity risk management literature. By considering a broad spectrum of predictive models for commodity futures returns, we aim to equip the selective hedging framework with a diverse set of forecasts as inputs, giving it a fair chance to succeed.

We implement the hedges on 24 commodities spanning various sectors (agriculture, energy, livestock, and metals). The effectiveness of the hedges is gauged in terms of the out-of-sample mean-variance utility gain of hedging versus no-hedging. Commodity by commodity, each selective hedge is confronted with a traditional hedge and the statistical significance of differences in their expected utility gains is assessed via the McCracken and Valente (2018) test.

The empirical findings suggest that selective hedging struggles to outperform traditional hedging in terms of expected utility gains. As a result, commodity producers are often better off assuming no changes in futures prices over the hedging horizon. The limited out-of-sample predictability of individual commodity futures returns hinders the ability of selective hedging to deliver superior utility gains: the speculative component tends to increase risk compared to traditional hedging, while failing to provide additional returns. This issue is further aggravated by transaction costs. These findings are reaffirmed by a range of robustness tests that consider alternative hedge ratio designs, time-varying risk aversion, expected utility gains over sub-samples, longer estimation windows to generate forecasts, long and short hedging strategies, different rebalancing frequencies, longer-dated futures contracts, and the hedging needs of a multi-commodity producer.

The main takeaway from this paper is that, although selective hedging emerges as the optimal solution in theoretical models, it is challenging for commodity firms to obtain a higher utility from its practice compared to traditional hedging. Our study, therefore, strongly recommends that risk managers focus on hedging spot price risk without incorporating their market views into the strategy. Additionally, traditional hedging does not rely on return forecasts and is thus straightforward to implement, reinforcing its appeal.

Our study speaks to the selective hedging literature that builds upon the theoretical models of Anderson and Danthine (1981, 1983) and Stulz (1984) with empirical implementations in Cotter and Hanly (2010, 2012), Furió and Torró (2020) and Barroso et al. (2022).[1] Our main finding on the difficulty of significantly and reliably outperforming traditional hedging aligns also with a selective hedging literature that documents the very small increase in firm value accrued from selective hedging (Adam and Fernando, 2006; Brown et al., 2006) and warns against the perils of poorly structured selective hedging programs (Chalmin, 1987; Pirrong, 1997; Carter et al., 2021; Westgaard et al., 2022).[2]

Moreover, our work contributes to the literature on the time-series predictability of individual commodity returns. Bessembinder and Chan (1992) provide evidence that several predictors of stock and bond returns have in-sample predictive content for commodity futures returns, while Bjornson and Carter (1997) extend this evidence to additional predictors and agricultural commodity returns. Both papers argue that the observed predictability aligns with conditional pricing models. In contrast, the evidence on out-of-sample predictability of commodity returns is less conclusive. Hollstein et al. (2021) contend that business cycle and commodity characteristics can predict individual commodity returns. However, Ahmed and Tsvetanov (2016) and Guidolin and Pedio (2021) assert that the predictability of individual commodity returns is, at best, very low,

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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 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.

[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 speculation in crude oil futures. Carter et al. (2021) examines Queensland Sugar Limited's losses, concluding that selective hedging was the culprit. Westgaard et al. (2022) examine 14 commodity trading disasters which include those by China Aviation Oil (Singapore) or the State Reserves Bureau (China) where selective hedging led to dramatic losses. In 2022, Tsingshan Holding Group lost $8 billion on suspicion of selective hedging in the nickel futures markets (The Economist, 2022).

while Wang and Zhang (2024) find mixed evidence using sophisticated machine learning methods. Using a zero-return (no-predictability) expectation as the benchmark – which is appropriate for this study as it aligns with the assumptions implicit in traditional hedging – we confirm that individual commodity futures returns exhibit weak out-of-sample predictability.

The rest of the article unfolds as follows. Sections 2 and 3 introduce the methodology and data, respectively. Section 4 discusses the expected utility gains of the various hedges and explains the failure of selective hedging. Section 5 presents robustness checks and Section 6 concludes.

2. Hedging Framework

2.1. Optimal hedging under mean-variance utility

We consider the canonical problem of a single commodity producer that builds a hedge at time t and rebalances it at $t+1$. As in prior studies, we abstract from uncertainty in the producer's output. Following the theoretical framework of hedging laid out by Anderson and Danthine (1981), we assume a mean-variance utility function for the commodity firm formalized as

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

where $\Delta p_{t+1} = \Delta s_{t+1} - h_t \Delta f_{t+1}$ is the time t to t+1 logarithmic return of the hedge portfolio, Δs_{t+1} is the spot return, Δf_{t+1} is the futures return, h_t is the optimal hedge ratio that defines the number of short futures positions per unit of expected output or spot position, and the parameter γ is the coefficient of risk aversion of our representative hedger.

The maximization of the hedger's expected utility conditional on the information set available at time t, denoted Ω_t, gives the optimal selective hedge ratio as

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

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

The selective hedge is made up of a minimum-variance component, β_t, and a speculative component, $\frac{E_t(\Delta f_{t+1}|\Omega_t)}{\gamma\sigma_{f,t}^2}$. Thus, a commodity producing firm 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 the firm anticipates a fall in the futures price ($E_t(\Delta f_{t+1}|\Omega_t) < 0$), the number of short futures contracts will be higher than under pure hedging, $h_t > \beta_t$. The utility-maximizing hedge ratio collapses to the minimum-variance hedge ratio, $h_t = \beta_t$, if the hedger is infinitely risk averse, $\gamma = \infty$, or the futures price is assumed to follow a pure random walk, $E_t(\Delta f_{t+1}|\Omega_t) = 0$. Using a window of past L observations at each hedge formation time t, we operationalize β_t as the OLS slope coefficient from a regression of spot returns on futures returns (Ederington, 1979), which we refer to as the minimum variance, or MinVar, hedge. Other approaches for the traditional hedge ratio are considered in the robustness tests section.

2.2. Competing selective hedging strategies

Selective hedging requires a forecast of the futures return, as formalized in Equation (2). A simple approach is to use the historical average (HistAve) of the futures return, $E_t(\Delta f_{t+1}|\Omega_t) = \frac{1}{L}\sum_{j=0}^{L-1}\Delta f_{t-j}$, based on the assumption that the futures price follows a random walk with drift. To our knowledge, this form of selective hedging has not been explored in prior studies. In line with Cotter and Hanly (2010, 2012), we also utilize the autoregressive (AR) selective hedge where the forecast is given by $E_t(\Delta f_{t+1}|\Omega_\mathrm{t}) = \hat{\alpha}_{0,t} + \hat{\alpha}_{1,t}\Delta f_t$ with $\hat{\alpha}_{0,t}$ and $\hat{\alpha}_{1,t}$ representing the model parameters which are estimated at each time t using historical futures returns $\{\Delta f_{t-j}\}_{j=0}^{L-1}$. Building on Furió and Torró (2020), we extend this to a vector autoregressive (VAR) selective hedge, utilizing a futures return forecast derived from a bivariate VAR(p) model fitted to historical futures returns and roll yields. These selective hedging strategies rely on a limited information set, Ω_t.

Next, we implement selective hedges utilizing a larger information set, Ω_t, with K predictors. A novel approach involves the equal-weight combination (EWC) of univariate regression forecasts, as advocated by Rapach et al. (2010) for equities and Hollstein et al. (2021) for commodities. Specifically, the futures return forecast is computed as $E_t(\Delta f_{t+1}|\Omega_t) = \boldsymbol{\omega}_t' \Delta \hat{\boldsymbol{f}}_{t+1}$ where $\boldsymbol{\omega}_t' = \left(\frac{1}{K}, \dots, \frac{1}{K}\right)$, and $\Delta \hat{\boldsymbol{f}}_{t+1} = \left(\Delta \hat{f}_{1,t+1}, \dots, \Delta \hat{f}_{K,t+1}\right)'$ with $\Delta \hat{f}_{k,t+1} = \hat{a}_{0,t} + \hat{a}_{1,t} z_{k,t}$ denoting the individual forecasts conditioned upon each of the predictors $\boldsymbol{z}_t = \left(z_{1,t}, z_{2,t}, \dots, z_{K,t}\right)'$.

Inspired by the optimal currency overlay strategy proposed by Barroso et al. (2022), we implement a selective hedge based on the seminal style-integration framework of Brandt et al. (2009) which blends multiple asset characteristics to proxy for expected returns. The hedger solves the problem

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

where Δs_{t+1}, Δf_{t+1}, and $\Delta p_{t+1}^{K-Integr}$ denote the spot, futures and K-Integr hedge returns from time t to $t+1$ for the commodity in question. β_t denotes the MinVar hedge ratio of the commodity estimated at time t, $\boldsymbol{\omega}_t$ is a $K \times 1$ vector of loadings estimated at time t, and $\boldsymbol{z}_t = \left(z_{1,t}, z_{2,t}, \dots, z_{K,t}\right)'$ are K predictors. For each predictor $k = 1, \dots, K$, we standardize the time-series data $\{z_{k,t-j}\}_{j=0}^{L-1}$ to have a mean of zero and a standard deviation of one. We adopt a tracking error constraint $\sigma\left(\Delta p_{t+1}^{MinVar} - \Delta p_{t+1}^{K-Integr}(\boldsymbol{\omega}_t)\right) \leq \varsigma$, where $\sigma(\cdot)$ denotes the standard deviation, Δp_{t+1}^{MinVar} is the traditional MinVar hedge return, and ς is the tracking error threshold. This ensures that the K-Integr portfolio does not deviate substantially from the benchmark MinVar portfolio. The K-Integr selective hedge represents a novel approach in the context of commodity hedging.

Lastly, by allowing for complex nonlinear relationships between candidate predictors and target futures returns, ML methods can be a fruitful approach to construct selective hedges. The ML forecast of the futures return is generated as $E_t(\Delta\boldsymbol{f}_{t+1}|\Omega_t) = g^*(\boldsymbol{Z}_t)$ where $g^*(\cdot)$ is the nonlinear function implicit in the ML method used. We deploy the ML methods with pooled data across commodities to increase the sample size. Accordingly, the $N \times 1$ vector $\Delta\boldsymbol{f}_{t+1}$ represents the futures return at time t+1 for each of the N commodities, while $\boldsymbol{Z}_t$ contains the values of the K predictors, $(z_{1,t}, z_{2,t}, \ldots, z_{K,t})$, pooled across commodities. We standardize the time-series data for each commodity prior to pooling. Consistent with the empirical ML literature (Fischer and Krauss, 2018; Gu et al., 2020; Chen et al., 2023; Rad et al., 2023), the nonlinear function $g^*(\cdot)$ is implemented using supervised ML algorithms. Random forests (RF) are used in the main analysis, while deep neural networks (DNN), either alone or in combination with long-short term memory (LSTM) units, are employed in the robustness section. To the best of our knowledge, these ML hedges are novel in the risk management literature. Table 1 lists all the selective hedging strategies.

[Insert Table 1 around here]

2.3. Hedging effectiveness

We assess the effectiveness of the hedging strategies according to the expected utility gain, defined as the difference in expected utility between the hedge portfolio and the unhedged spot position

$$\Delta E(U_{Hedge}) = E(U_{Hedge}) - E(U_{Spot}), \tag{4}$$

where $U(\cdot)$ represents the mean-variance utility function from Equation (1). By adopting the expected utility gain instead of other portfolio performance metrics, such as the Sharpe ratio, we can consistently measure hedging effectiveness using the same risk aversion assumption as in the hedge ratio construction (Equation (2)). Risk aversion is set to a constant value of $\gamma = 5$ in the main analysis, while a time-varying γ_t is used in the robustness tests.

To assess the statistical significance of the difference in hedging effectiveness between the MinVar and selective hedging (SH) strategies, we employ the McCracken and Valente (2018) test with the null hypothesis $H_0\colon \Delta E\left(U_{Diff}\right) = \Delta E(U_{SH}) - \Delta E(U_{MinVar}) \leq 0$ and the alternative hypothesis $H_1\colon \Delta E\left(U_{Diff}\right) > 0$ where $\Delta E(U)$ is the expected utility gain from Equation (4). The inference is based on the stationary bootstrap method of Politis and Romano (1994). Using a moving block bootstrap approach as in Patton et al. (2009), we generate $B = 500$ artificial samples of spot returns, futures returns and predictors, denoted as $\{\Delta s_{t,b}\}_{t=1}^{T}$, $\{\Delta f_{t,b}\}_{t=1}^{T}$, $\{\boldsymbol{z}_{t,b}\}_{t=1}^{T}$, for $b = 1, \dots, B$. The demeaned distribution $\left\{\Delta U_{Diff,b}^{*}\right\}_{b=1}^{B}$ provides the bootstrap p-value for the test.

3. Data

The 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 LSEG Datastream, respectively. The spot returns are measured as weekly changes in logarithmic (log) spot prices. Assuming full collateralization of futures positions, the futures returns are calculated as weekly log price changes plus the risk-free rate, $\Delta f_{t+1} = \left(f_{t+1,M} - f_{t,M}\right) + r_{F,t+1}$ where $f_{t,M}$ denotes the week t log price of the futures contract with maturity M, and $r_{F,t+1}$ represents the 1-month U.S. Treasury bill rate, serving as a proxy for the risk free rate. We create time-series of futures prices per commodity using the front-end contract until the maturity month when we roll to the second-nearest contract. The summary statistics for spot and futures returns in Table 2 confirm various stylized facts: negligible expected returns, and large cross-sectional heterogeneity in spot price risk and basis risk as conveyed by the return variance and spot-futures correlation, respectively.

[Insert Table 2 around here]

Additionally, we collect weekly data on $K = 37$ variables used as predictors in the EWC, K-Integr, and ML selective hedges. These variables pertain to two groups. The first group contains 10 commodity futures characteristics identified in the literature as relevant for their pricing ability, primarily on a cross-sectional basis. The second group includes 27 financial, macroeconomic, and sentiment indicators that reflect the overall state of the economy, capturing financing costs and short-term imbalances between commodity demand and supply. Appendix A offers a detailed description of each of the 37 predictive variables, including data sources and key references.

4. Main Empirical Results

4.1. Commodity hedge ratios

The hedging strategies are implemented sequentially out-of-sample (OOS) to simulate the real-time hedging decisions of a representative single-commodity producer. At each sample week *t*, the covariance, $\sigma_{sf,t}$, variance, $\sigma_{f,t}^2$, and the futures return forecast, $E_t(\Delta f_{t+1}|\Omega_t)$, are obtained from a L-length window of past data to construct the hedge ratio, Equation (2). The hedge portfolio is held from week *t* to week *t*+1, after which the estimation window is moved forward by one week to form a new hedge portfolio at week *t*+1, and this process continues iteratively.

In our primary analysis, hedges are rebalanced weekly using rolling L-length windows of historical data (L = 520 weeks) for parameter estimation. For the VAR(p) selective hedge, the optimal lag order p (with a maximum of 12) is determined by minimizing the Akaike Information Criterion (AIC) in each rolling window, following Furió and Torró (2020). For the K-Integr selective hedge, we begin by applying a strict tracking error threshold of ς = 2% p.a., as in Barroso et al. (2022).

Following the approach of Gu et al. (2020), the RF forecasts are obtained as follows. First, we divide the sample into a training set, consisting of the first 60% of the L-week estimation window, and a validation set, comprising the most recent 40% of the window. Within each set, we pool across commodities the standardized time-series for the *K* predictors and the target futures returns. Next, we optimize the RF for each of various hyperparameter[3] combinations on the training set and evaluate its performance using the mean squared error (MSE) on the validation set. The hyperparameters yielding the lowest MSE are then used to optimize the RF over the entire estimation sample (training and validation). This optimized RF is subsequently employed to construct the OOS futures return forecast. The RF model is updated annually, with the first optimization carried out in the last week of September 2013 using the initial 520-week window, followed by updates on the last week of each September.

Figure 1 illustrates the evolution of the resulting traditional and selective hedge ratios for cocoa. Figure 2 presents the standard deviations of the hedge ratios on average across commodities. The MinVar hedge ratio is rather stable as suggested by a standard deviation of 4% on average across commodities in Figure 2. The selective hedge ratios are far more volatile and prone to abrupt changes (c.f., Figure 1), especially those that hinge on RF forecasts (standard deviation of 56% on average in Figure 2), VAR forecasts (54%) and AR forecasts (32%) with the HistAve and K-Integr forecasts providing the least volatile selective hedge ratios (16% and 12%, respectively). The relatively low volatility of the K-Integr hedge ratios is not surprising given the stringent tracking error constraint. Naturally, more volatile hedge ratios will be penalized by higher rebalancing costs.

[Insert Figures 1 and 2 around here]

4.2. Hedging effectiveness

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[3] The number of trees, *S,* is set to 300. Hyperparameters include the number of predictors per simulation, $R = \{3, 5, 10, 20, 30\}$, and the maximum number of branches or tree depth, $D = \{1, 2, 3, 4, 5, 6\}$.

Table 3 illustrates the hedging effectiveness of each commodity, as derived from Equation (4). Table 3, Panel E shows that the MinVar and K-Integr hedges achieve the highest average expected utility gains, at 16.27% per annum (p.a.) and 16.61% p.a., respectively. In contrast, the HistAve, EWC, AR, VAR, and RF hedges demonstrate lower hedging effectiveness, with average expected utility gains of 15.73%, 15.72%, 13.31%, 9.22%, and 7.28% p.a., respectively.

[Insert Table 3 around here]

Table 3 also includes the p-values from the McCracken and Valente (2018) test, which evaluates the difference in expected utility gains between selective and traditional hedging strategies. The generally sizeable p-values indicate that selective hedging often does not provide superior expected utility gains compared to the MinVar hedge. Given the simplicity of traditional hedging, along with the limited evidence in favor of selective hedging, we advise commodity producers to focus on hedging spot price risk without incorporating their market views into their hedging program.

Incorporating transaction costs into the analysis, we calculate the net returns of the hedge portfolios 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 transaction cost (TC) estimate of 8.6 basis points from Marshall et al. (2012). We then compute the net expected utility gain for each strategy using Equation (4). The results, presented in Table 3, Panel E, show that transaction costs have a minimal impact on the expected utility gain of the MinVar hedge, reducing it by only 0.05% p.a. In contrast, transaction costs decrease the expected utility gains of the HistAve, EWC, K-Integr, RF, AR, and VAR hedges by 0.08%, 0.19%, 0.32%, 0.51%, 1.05%, and 1.61% p.a., respectively. Thus, the consideration of transaction costs reinforces our previous finding.

4.3. Understanding the hedging effectiveness of traditional hedging

Next, we aim to understand why selective hedging does not significantly enhance the hedger's utility. To do this, we adopt the R_{OOS}^2 metric from Campbell and Thompson (2008) to assess the statistical accuracy of forecasts under a mean squared error loss function, defined as follows

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

where $\widehat{\Delta f}_{t+1}^{MinVar} = 0$ represents the no-predictability assumption (zero expected commodity futures return) underlying the traditional hedging strategy, and $\widehat{\Delta f}_{t+1}^{SH}$ is the forecast used to determine the speculative component in Equation (2) and to form the selective hedge.[4] A value $R_{OOS}^2 \leq 0$ indicates that the forecasts are not more accurate than the benchmark, while $R_{OOS}^2 > 0$ suggests they are more accurate. We test the statistical significance of these findings using the Diebold and Mariano (1995) test for the null hypothesis $H_0: E(d_t) \leq 0$ against $H_1: E(d_t) > 0$ where $d_t = \Delta f_{t+1}^2 - \left(\Delta f_{t+1} - \widehat{\Delta f}_{t+1}^{SH}\right)^2$ is the squared error differential. The evidence presented in Table 4 indicates limited predictability: the commodity futures return forecasts used in the selective hedges are not more accurate than the zero expected return assumed in the MinVar hedge.

[Insert Table 4 around here]

To investigate whether selective hedging captures additional returns beyond traditional hedging, we estimate spanning regressions of the selective hedge portfolio returns on the MinVar hedge portfolio returns. The regression intercept (alpha) reflects the extra return from incorporating the hedger's view of the commodity futures market into the hedging strategy. Table 5 presents the annualized alphas along with Newey-West adjusted *t*-statistics. While the K-Integr and RF hedges

[4] The futures return forecast that is implied from the K-Integr selective hedge, Equation (3), is $\boldsymbol{\omega}_t' \boldsymbol{z}_t = E_t(\Delta f_{t+1} | \Omega_t) / \left(\gamma\, \sigma_{f,t}^2\right)$, which can be rewritten as $E_t(\Delta f_{t+1} | \Omega_t) = \gamma\, \sigma_{f,t}^2 (\boldsymbol{\omega}_t' \boldsymbol{z}_t)$.

demonstrate some success with several positive alphas, the overall statistical significance of the alphas is, at best, very weak. This aligns with the limited predictability that we documented earlier, reinforcing the evidence that selective hedging struggles to consistently capture additional returns.

[Insert Table 5 around here]

How does the risk reduction ability of selective hedging compare with that of traditional hedging? To address this question, we compare the variance of the selective and traditional hedge portfolio returns. Following the approach of Wang et al. (2015), we use the Diebold and Mariano (1995) test to assess statistical significance. The null hypothesis is $H_0\colon E\left[(\Delta p_t^{SH})^2 - (\Delta p_t^{MinVar})^2\right] \leq 0$ and the alternative hypothesis is $H_1\colon E\left[(\Delta p_t^{SH})^2 - (\Delta p_t^{MinVar})^2\right] > 0$ where $(\Delta p_t^{SH})^2$ and $(\Delta p_t^{MinVar})^2$ are the squared returns of the selective and traditional hedge portfolios, respectively.

Table 6 presents the annualized hedge portfolio variances alongside with the *p*-values from the Diebold and Mariano (1995) test. The findings underscore that the MinVar hedge portfolio, with an average variance of 3.37% p.a. across commodities, provides the most effective risk reduction. In contrast, selective hedge portfolios exhibit higher variances, ranging from 3.45% (K-Integr hedge) to 8.46% (RF hedge) p.a. Moreover, the small *p*-values indicate that selective hedging substantially increases risk compared to traditional hedging.[5] Thus, the primary goal of covering the risk of the spot position is undermined by selective hedging. Altogether, the combination of return benefits that are, at best, marginal (as shown in Table 5) and elevated risk (Table 6) renders selective hedging an unattractive and potentially hazardous strategy for commodity producers.

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[5] We evaluated downside risk of the various hedge portfolios using maximum drawdown and 1% Gaussian Value at Risk (VaR) metrics. The MinVar hedge had the lowest maximum drawdown (11.67%) and least negative 1% VaR (-4.78%) on average across commodities. In contrast, the selective hedges had maximum drawdowns between 11.92% and 22.11%, with 1% VaR values ranging from -8.75% to -4.90%.

[Insert Table 6 around here]

There is an exceptional commodity, natural gas, for which selective hedging (with the HistAve and EWC forecasts) improves upon the traditional hedging effectiveness significantly at the 5% level as borne out by the expected utility gains (Table 3). The increase in expected utility stems from the significant return capture of the selective hedges (Table 5) for the same level of risk (Table 6).[6]

While selective hedging is theoretically optimal, its practical effectiveness compared to traditional hedging is challenging to achieve. This is primarily because it demands more accurate forecasts of commodity futures returns than the zero-return assumption that underlies traditional hedging. As the evidence shows, since the higher risks incurred are not accompanied by a significant increase in returns, selective hedging often fails to provide added value for commodity producers. Hence, we recommend that commodity producers adhere to the simpler traditional hedging approach.

5. Robustness Tests

We now modify elements of the empirical design to reassess the effectiveness of selective versus traditional hedging. Each modification alters one aspect, holding all else constant. For brevity, we present average results across commodities, with disaggregated results available upon request.

5.1. *Alternative designs of the traditional hedge ratio*

According to the theoretical framework developed by Anderson and Danthine (1981), the first component of the quadratic utility-maximizing hedge ratio, β_t in Equation (2), is the traditional

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[6] The natural gas industry has undergone a dramatic transformation during the sample period through the shale gas revolution that increased supply and induced a downward trend in prices. As shown in Table 2, by contrast with all other commodities, the expected return of natural gas futures contracts is not negligible but a significantly negative -33.62% p.a. which is more difficult to reconcile with the zero-return expectation, $E_t(\Delta f_{t+1}|\Omega_t) = 0$, that underlies the traditional hedge.

minimum variance hedge ratio. This ratio depends on two (co)variance parameters, $\sigma_{sf,t}$ and $\sigma_{f,t}^2$. Since Ederington's (1979) seminal work, linear OLS regression has been widely employed to consistently estimate β_t which is used as the MinVar hedge ratio in our main analysis.

Wang et al. (2015) compare the naïve one-to-one hedge ratio, which serves as a proxy for β_t under the assumption of no basis risk ($\sigma_{sf,t} = \sigma_{f,t}^2$), with various estimates of the minimum-variance hedge ratio β_t. Their analysis shows that, in an out-of-sample setting, the risk reduction provided by the naïve one-to-one hedge ratio is difficult to surpass using estimated minimum variance hedge ratios, largely due to estimation error and model misspecification. We now operationalize β_t in additional ways: (a) using the one-to-one hedge ratio, and (b) through various refinements of the OLS regression model, including the bivariate VAR model, bivariate VEC model, bivariate DCC-GARCH model, bivariate BEKK-GARCH model, and Markov-switching regression model.[7]

Table 7 presents the expected utility gains for both traditional and selective hedges based on the different specifications of β_t. The evidence that selective hedging struggles to consistently outperform traditional hedging remains compelling. The expected utility gain of traditional hedging is 16.33% p.a. on average across commodities and specifications of β_t. In comparison, the corresponding selective hedges show expected utility gains of 16.66% (K-Integr), 15.62% (HistAve), 15.60% (EWC), 13.48% (AR), 9.62% (VAR), and 7.15% (RF) p.a. also on average.

[Insert Table 7 around here]

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[7] Specifically, we estimate a bivariate VAR(1,1) model for spot and futures returns, a bivariate VEC(1,1) model, a bivariate DCC-GARCH(1,1) model, a bivariate BEKK-GARCH(1,1), and the Markov regime-switching OLS hedge ratio that allows for high versus low volatility regimes.

Additionally, Table 7 shows that the expected utility gain of the MinVar hedge (16.27%) is comparable to that of the one-to-one hedge (15.97%). Unreported results, based on McCracken and Valente's (2018) p-values for the null hypothesis $H_0: \Delta E(U_{MinVar}) \leq \Delta E(U_{One-to-One})$ versus the alternative hypothesis H_1: $\Delta E(U_{MinVar}) > \Delta E(U_{One-to-One})$, reveal that, for most commodities, the MinVar hedge does not significantly outperform the naïve one-to-one hedge. Therefore, consistent with the findings of Wang et al. (2015), commodity producing firms might favor the simplicity of the one-to-one hedging strategy.

5.2. Alternative specifications of the selective hedging strategies

To give selective hedging a fair opportunity to outperform traditional hedging, we explore alternative designs for the selective hedge ratios. First, we examine variations of the EWC selective hedge ratio employed thus far with K=37 predictors. We apply the EWC selective hedge using only the 10 commodity-specific characteristics that are well established for their pricing ability, as well as a narrower subset of three asset characteristics – roll yield, momentum, and value – highlighted by Barroso et al. (2022). It turns out that narrowing the information set reduces the expected utility gain of the EWC selective hedge, as shown in the "K=10" and "K=3" columns of Table 8, Panel A. Hence, the challenge of consistently surpassing traditional hedging remains.

[Insert Table 8 around here]

Drawing on the stock return forecasting literature (Rapach et al., 2010; Rapach and Zhou, 2022), we deviate from the equal-weighting approach used in the EWC hedge by exploring alternative methods to combine univariate regression forecasts. Specifically, we weigh the forecasts by the inverse of their past mean squared error (MSE) or employ an Elastic Net (E-Net) algorithm; see e.g. Hollstein et al. (2021) and Rapach and Zhou (2022). Appendix B provides further details on the MSE and E-Net approaches. As shown in Table 8, Panel A, the EWC selective hedge remains highly competitive against the MSE and E-Net variants. Therefore, consistently outperforming the MinVar hedge remains a challenge with these two approaches as well.

Following Neely et al. (2014), we extract the principal component(s) from the full set of predictors ($K = 37$) and deploy two selective hedges which harness the predictive power of the first and first-two principal components, respectively. The expected utility gains of these hedges, denoted PC1 and PC1-2 in Table 8, Panel A, are not superior to those from traditional hedging either.

Next, we explore several variants of the K-Integr selective hedge, which emerged in our main analysis as the closest competitor to the traditional MinVar hedge. We begin by using the two subsets of commodity characteristics (K=10 and K=3) as predictors. We then incorporate Elastic Net (E-Net) regularization into the objective function, as detailed in Appendix C. Additionally, we experiment with a softer tracking error constraint, $\varsigma = \{ 5\%, 10\%\}$, which allows the K-Integr hedge to deviate more from the MinVar hedge than the former $\varsigma = 2\%$ in Table 3, thereby increasing the role of speculation. As shown in Table 8, Panel B, the expected utility gain of these K-Integr variants is comparable to that of the MinVar hedge. This finding underscores the challenge of achieving strong and consistent outperformance with selective hedging compared to the simpler MinVar hedge. Notably, when we increase the tracking error constraint, ς, to allow for a greater role of speculation, the expected utility gain of the K-Integr hedge decreases.

We also examine a variant of the K-Integr hedge that, aiming to enhance the estimation efficiency of the $K \times 1$ vector of loadings, $\boldsymbol{\omega}_t$, involves pooling across commodities the standardized time-series of K predictors.[8] The resulting estimate $\widehat{\boldsymbol{\omega}}_t$ utilizes a panel dataset, as opposed to the individual estimates $\widehat{\boldsymbol{\omega}}_{i,t}, i = 1, \ldots, N,$ outlined in Section 2 for the commodity-by-commodity K-Integr implementation. The results in the last column of Table 8, Panel B, indicate that the expected utility gain of the pooled K-Integr hedge averages 16.63% p.a. across commodities, which is nearly identical to the 16.61% p.a. average expected utility gain from the earlier K-Integr hedges shown in Table 3. Overall, the findings from the various K-Integr selective hedges suggest that it is generally not advantageous for commodity producers to abandon traditional hedging practices.

Next, we implement additional selective hedges that leverage forecasts from ML methods. To maintain consistency, we first apply RF using smaller subsets of commodity characteristics (*K*=10 or *K*=3) as predictors. Second, following Fischer and Krauss (2018), Gu et al. (2020), Chen et al. (2023), and Rad et al. (2023), we implement deep neural networks (DNN) with two hidden layers (DNN2, using 32 and 16 nodes per layer) and three hidden layers (DNN3, with 32, 16, and 8 nodes). These DNN architectures are then augmented with 4 or 8 long-short term memory (LSTM) units, designed to capture long-run nonlinear predictability patterns.[9] Table 8, Panel C, presents the results. None of these advanced selective hedges achieves a higher expected utility gain than the

[8] We deployed the pooled K-Integr hedge with cross-sectional standardization of commodity-specific predictors, following Brandt et al. (2009), and applied double (cross-section and time) standardization, yielding expected utility gains of 15.97% p.a. and 15.84% p.a., respectively. In all cases, the time-series of financial, economic, and sentiment predictors were also standardized. These results underscore that selective hedging struggles to significantly outperform the traditional MinVar hedging strategy.

[9] Following similar steps to the RF method described in Section 4.1, these ML methods are deployed with a maximum of 100 epochs, a batch size of 20% of the training sample, a patience level of 5, and learning rates of 0.001 or 0.01. Optimization is performed with the Adam optimizer and the Huber loss function (transition at the 99.9% quantile). Overfitting is controlled using early stopping, a 5% dropout layer, batch normalization, an ensemble of 500 networks, and *l2* regularization set at 10^{-5} or 10^{-3}. The number of LSTM units is based on the specifications in Chen et al. (2023) and Rad et al. (2023).

MinVar hedge, which is unsurprising given that the (unreported) R^2_{OOS} measures for the ML forecasts are generally negative or zero, indicating no improvement over the zero-return forecast benchmark. This finding aligns with the mixed results from Wang and Zhang (2024) regarding the predictive ability of ML methods for individual commodity futures returns and echoes Cakici et al. (2023), who question the effectiveness of ML in predicting stock returns.[10]

Since Bates and Granger's (1969) seminal paper, combining forecasts from different methods has been widely advocated to reduce out-of-sample mean squared error. Following this approach, we deploy a selective hedge (denoted Comb) that uses an equal-weighted combination of competing forecasts: HistAve, AR, VAR, EWC, K-Integr and RF. Although the Comb selective hedge shows some improvement, the traditional (MinVar) hedge remains difficult to beat.

Next, we implement a selective hedge based on futures return forecasts derived from Fama-MacBeth cross-sectional (CS) predictive regressions. First, we estimate each week the slopes from cross-sectional regressions of the commodity futures return at week *t* on commodity-specific characteristics at week *t*-1. The estimated cross-sectional slopes are then averaged over the 10 years preceding hedging decisions and these averages are used, alongside the most recent characteristics, to forecast commodity futures returns one week ahead. As shown in Table 8, Panel D, the CS selective hedge fails to outperform the MinVar hedge, regardless of the characteristics used.

[10] We compiled a comprehensive set of 140 predictors by combining financial, macroeconomic, and sentiment indicators used in the ML-based selective hedges (detailed in Appendix A, Panel B) with the FRED-MD variables from McCracken and Ng (2016), sourced from Prof. McCracken's website. From this extensive dataset, we extract eight principal components and combine them with 10 commodity-specific characteristics (Appendix A, Panel A). The expected utility gains for the different ML-based hedges either decrease or increase minimally, and thus they are still unable to significantly outperform the MinVar hedge.

Lastly, under the assumption that the futures curve remains unchanged, the roll yield today lends itself as a naïve forecast of the expected futures return. Thus, we construct a Naïve Basis selective hedge using the forecast $E_t(\Delta f_{t+1}|\Omega_t) = \frac{Roll\ yield_t}{D_t} \times 7$ where $Roll\ yield_t = f_{t,1} - f_{t,2}$, with $f_{t,1}$ and $f_{t,2}$ representing the log prices of the front and second-nearest contracts, respectively, and D_t the number of calendar days between their maturities. As shown in the last column of Table 8, Panel D, the Naïve Basis hedging strategy is not more effective than the traditional MinVar hedge.

5.3. Are the findings sample specific?

To assess whether our key finding is driven by a specific period within the sample, we classify the weeks into four subsamples: (i) pre- versus post-financialization (with January 2006 as the cutoff, as per Stoll and Whaley, 2010), (ii) backwardation versus contango (positive versus negative commodity-specific roll yields), (iii) U.S. recessions versus expansions (as defined by NBER), and (iv) high versus low volatility. The volatility split is determined relative to the median value of two volatility measures: the GARCH(1,1) volatilities of each commodity's spot returns and the macro uncertainty index from Jurado et al. (2015). The expected utility gains of the hedging strategies across these subsamples, presented in Table 9, reinforce our main conclusion that selective hedging strategies struggle to outperform traditional hedging. Additionally, our analysis aligns with economic intuition, suggesting that the utility commodity producers derive from hedging is particularly high during recessions, contango conditions, and periods of high market volatility.

[Insert Table 9 around here]

5.4. Non-constant risk aversion

Thus far, we have assumed a constant coefficient of relative risk aversion ($\gamma = 5$). We now generalize the selective hedge ratio to $h_t = \beta_t - \frac{E_t(\Delta f_{t+1}|\Omega_t)}{\gamma_t\, \sigma_{f,t}^2}$, using as γ_t the relative risk aversion estimates from Bekaert et al. (2022), which average 3.0624 over our sample period. Accordingly, the speculative term plays a larger (smaller) role in periods of low (high) risk aversion. The expected utility gains of the hedging strategies, as shown in Table 10, confirm that commodity producers are often better off sticking with the traditional MinVar hedge. The expected utility gain for MinVar (9.41% p.a.) is comparable to that of the K-Integr hedge (9.83% p.a.) and above those of the HistAve, EWC, RF, and AR hedges (8.58%, 8.54%, 6.01%, and 4.70% p.a., respectively). Notably, the VAR hedge results in a negative expected utility gain of -1.71% p.a., indicating that, in this scenario, the representative commodity producer would be better off not hedging at all.

[Insert Table 10 around here]

5.5. Estimation window and rebalancing frequency

Our investigation thus far has employed hedge ratios based on past rolling estimation windows of length $L = 520$ weeks (10 years), rebalanced weekly. The expected utility gains inferred from expanding windows (starting at 520 weeks and incrementally adding one week at a time), shown in Table 10, are quite similar to those derived from the rolling window setup in Table 3.

Given that the commodity hedging literature has predominantly utilized daily (Baillie and Myers, 1991), weekly (Cotter and Hanly, 2010, 2012; Wang et al., 2015), or monthly (Cotter and Hanly, 2010, 2012; Furió and Torró, 2020) hedging frequencies, our adoption of weekly rebalancing offers a reasonable middle ground.[11] We now examine monthly and quarterly rebalancing. As shown in Table 10, lower rebalancing frequencies enhance utility for both traditional and selective hedging strategies. However, the selective hedges do not significantly outperform the MinVar hedge.

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[11] Bodnar et al. (1998) document large firm heterogeneity in hedging frequency from surveys of 399 non-financial firms; 28% revalue their derivatives portfolios daily or weekly, 27% monthly, 21% quarterly and 5% annually. The remaining firms rebalance their hedges on an *ad-hoc* basis.

5.6. Alternative futures maturities

We have implemented the hedges with front-end futures contracts. As a robustness check, we employ the second, third, fourth, fifth, or sixth maturity contracts along the futures curve. Each contract is held until the last day of the month preceding the maturity of the front-end contract, at which point the position is rolled to the then third, fourth, fifth, sixth, or seventh contract, respectively. The results shown in Table 10 corroborate across maturities the difficulty of outperforming the MinVar hedge. For a given hedging method, the expected utility gains tend to decrease with the maturity of the hedging instruments, likely due to an increase in basis risk.

5.7. Long hedging

Our representative firm thus far has been a commodity producer, with the traditional hedge being short. We now address the hedging problem from the perspective of a processor or consumer of the physical commodity (long hedger). In this case, the hedge portfolio return is given by $\Delta p_{t+1} = -\Delta s_{t+1} + h_t \Delta f_{t+1}$. The selective hedge ratio that maximizes expected utility is $h_t = \beta_t + \frac{E_t(\Delta f_{t+1}|\Omega_t)}{\gamma\, \sigma_{f,t}^2}$ where the first component, $\beta_t = \frac{\sigma_{sf,t}}{\sigma_{f,t}^2}$, represents the traditional MinVar hedge ratio, and the second component caters for the speculative goal.

The last row of Table 10 presents the expected utility gains for long hedges. Over the sample period, the expected utility gain from short hedging is, on average, 4.87 percentage points higher annually than that from long hedging across commodities and hedging strategies. However, this average conceals significant heterogeneity. For instance, unreported results reveal that for natural gas, the expected utility gain from short hedging exceeds that from long hedging by 53.47 percentage points on average across hedging strategies. Conversely, for unleaded gasoline, the expected utility gain from long hedging is 26.69 percentage points higher than that from short hedging. Despite this variability, our main conclusion remains unchanged: selective hedging is not consistently superior to traditional hedging for commodity consumers either.

5.8. Hedging problem of a diversified producer

Our paper follows the commodity hedging literature in formalizing and examining empirically the hedging problem of a single-commodity producer (e.g., Ederington, 1979; Anderson and Danthine, 1981, 1983; Pirrong, 1997; Cotter and Hanly, 2010, 2012; Wang et al., 2015; Furió and Torró, 2020; Carter et al., 2021). Inspired by the cross-currency hedging setting of Barroso et al. (2022), we now consider a firm that produces all $N = 24$ commodities. Without loss of generality, we assume that the diversified commodity producer has equal exposure $1/N$ to the commodities. The cross-commodity K-Integr hedger solves the problem

$$\max_{\boldsymbol{\omega}_t} E_t\left[U\left(\widetilde{\Delta p}_{t+1}^{K-Integr}(\boldsymbol{\omega}_t)\right)\middle|\Omega_t\right], \tag{6}$$

subject to the tracking error constraint $\sigma\left(\widetilde{\Delta p}_{t+1}^{MinVar} - \widetilde{\Delta p}_{t+1}^{K-Integr}(\boldsymbol{\omega}_t)\right) \leq \varsigma$. Here, the loadings $\boldsymbol{\omega}_t$ are the solution that maximizes the expected utility of the cross-commodity hedge portfolio return

$$\widetilde{\Delta p}_{t+1}^{K-Integr}(\boldsymbol{\omega}_t) = \frac{1}{N}\sum_{i=1}^{N}\left(\Delta s_{i,t+1} - \left(\beta_{i,t} - \sum_{k=1}^{K}\omega_{k,t}z_{i,k,t}\right)\Delta f_{i,t+1}\right) = \tag{7}$$

$$\frac{1}{N}\sum_{i=1}^{N}\Delta s_{i,t+1} - \left[\frac{1}{N}\sum_{i=1}^{N}\beta_{i,t}\Delta f_{i,t+1} - \frac{1}{N}\sum_{i=1}^{N}\left(\sum_{k=1}^{K}\omega_{k,t}z_{i,k,t}\right)\Delta f_{i,t+1}\right],$$

where the ith commodity spot return and futures return are given by $\Delta s_{i,t+1}$ and $\Delta f_{i,t+1}$, and the MinVar hedge ratio by $\beta_{i,t}$. The return of the cross-commodity MinVar portfolio is given by $\widetilde{\Delta p}_{t+1}^{MinVar} = \frac{1}{N}\sum_{i=1}^{N}\left(\Delta s_{i,t+1} - \beta_{i,t}\Delta f_{i,t+1}\right)$ which can be derived from Equation (7) by setting $\boldsymbol{\omega}_t = 0$ to exclude the speculative component. The cross-commodity K-Integr hedge constraints the parameters $\boldsymbol{\omega}_t = (\omega_{1,t}, \dots, \omega_{K,t})'$ to be equal across commodities. This approach resembles the original parametric portfolio policies (PPP) method, where the vector of loadings on asset characteristics is common across assets over time (Brandt et al., 2009; Barroso et al., 2022).[12]

Unreported results show that the cross-commodity K-Integr hedge marginally outperforms the cross-commodity MinVar hedge, with expected utility gains of 4.00% p.a. compared to 3.48% p.a., respectively. However, this difference is not statistically significant, as confirmed by the McCracken and Valente (2018) test (p-value of 0.26). Therefore, selective hedging does not offer a significant advantage over traditional hedging for a diversified commodity producer either.

These results are not necessarily at odds with the commodity risk premia literature (e.g., Miffre and Rallis, 2007; Basu and Miffre, 2013; Szymanowska et al., 2014; Fernandez-Perez et al., 2018; Boons and Prado, 2019; Gu et al., 2023). In these studies, different characteristics rank a cross-section of commodities into top and bottom quintiles, which determine the equally-weighted long and short positions. In contrast, the K-Integr hedge portfolio is governed by a pure hedge ratio and a speculative ratio, with point forecasts of futures returns, $E_t(\Delta f_{t+1}|\Omega_t)$, and the futures return variance, $\sigma_{f,t}^2$, per commodity as key drivers.

6. Conclusions

This article provides a comprehensive analysis of traditional versus selective hedging strategies in commodity futures markets. Our findings show that incorporating speculative elements into hedging does not yield significant improvements in expected utility gains compared to the

[12] Excluding the spot return, the cross-commodity K-Integr portfolio is comparable to the PPP portfolio, as both optimally tilt a benchmark portfolio. However, while K-Integr employs a broader set of predictors, including commodity characteristics, financial, macroeconomic, and sentiment variables, to determine the optimal deviations from the benchmark, the PPP framework relies exclusively on asset characteristics.

traditional minimum-variance approach. The main challenge of selective hedging is the need for accurate point forecasts of commodity futures returns, which is inherently difficult. As a result, the speculative component adds risk to the hedge portfolio without delivering additional returns. The findings are consistent across a wide range of commodities, forecasting methods, hedge ratios, estimation window lengths, sample periods, futures maturities, and rebalancing frequencies.

The paucity of evidence supporting selective hedging over traditional hedging aligns with concerns raised in case studies of speculative-led commodity hedging fiascos (Pirrong, 1997; Carter et al., 2021; Westgaard et al., 2022) and is consistent with findings showing modest gains in firm value from selective hedging (Adam and Fernando, 2006; Brown et al., 2006). While private information may improve selective hedging, the key takeaway is that firms without reliable access to such information are generally better off adhering to traditional hedging practices without speculation.

References

Adam, T., and Fernando, C., 2006, Hedging, speculation, and shareholder value, *Journal of Financial Economics* 81, 283-309.

Ahmed, S., and Tsvetanov, D., 2016, The predictive performance of commodity futures risk factors, *Journal of Banking and Finance* 71, 20–36.

Anderson, R., and Danthine, J.-P., 1981, Cross hedging, *Journal of Political Economy* 89, 1182-1196.

Anderson, R., and Danthine, J.-P., 1983, Hedger diversity in futures markets, *Economic Journal* 93, 370-389.

Asness, C., Moskowitz, T., and Pedersen, L., 2013, Value and momentum everywhere, *Journal of Finance* 68, 929-985.

Baillie, R. T., and Myers, R. J., 1991, Bivariate GARCH estimation of the optimal commodity futures hedge, *Journal of Applied Econometrics* 6, 109-124.

Bakshi, G., Panayotov G., and Skoulakis, G., 2014, In search of explanation for the predictive ability of the Baltic Dry Index for global stock returns, commodity returns, and global economic activity, SSRN Working Paper http://dx.doi.org/10.2139/ssrn.1747345.

Barroso, P., Reichenecker, J. A., and Menichetti, M. J., 2022, Hedging with an edge: K-parametric currency overlay, *Management Science* 68, 669-689.

Bartram, S., 2019, Corporate hedging and speculation with derivatives, *Journal of Corporate Finance* 57, 9-34.

Basu, D., and Miffre, J., 2013, Capturing the risk premium of commodity futures: The role of hedging pressure, *Journal of Banking and Finance* 37, 2652-2664.

Bates, J. M., and Granger, C.W., 1969, The combination of forecasts, *Journal of the Operational Research Society* 20, 451-468.

Bekaert, G., Engstrom, E., and Xu, N., 2022, The time variation in risk appetite and uncertainty, *Management Science* 68, 3975-4004.

Bessembinder, H., and Chan, K., 1992, Time-varying risk premia and forecastable returns in futures markets, *Journal of Financial Economics* 32, 169-193.

Bjornson, B., and Carter, C., 1997, New evidence on agricultural commodity return performance under time-varying risk, *American Journal of Agricultural Economics* 79, 918-930.

Bodnar, G., Hayt, G., and Marston, R., 1998, Wharton survey of financial risk management by US non-financial firms, *Financial Management* 27, 70-91.

Boons, M., and Prado, M., 2019, Basis-momentum, *Journal of Finance* 74, 239-279.

Brandt, M., Santa-Clara, P., and Valkanov, R., 2009, Parametric portfolio policies: Exploiting characteristics in the cross-section of equity returns, *Review of Financial Studies* 22, 3444-3447.

Brown, G. W., Crabb, P. R., and Haushalter, D., 2006, Are firms successful at selective hedging *Journal of Business* 79, 2925-2949.

Cakici, N., Fieberg, C., Metko, D., and Zaremba, A., 2023, Machine learning goes global: Cross-sectional return predictability in international stock markets, *Journal of Economic Dynamics and Control* 155, 104725.

Campbell, J. Y., and Thompson, S. B., 2008, Predicting excess stock returns out of sample: Can anything beat the historical average? *Review of Financial Studies* 21, 1509-1531.

Carter, C. A., Schaefer, K. A., and Scheitrum, D., 2021, Raising cane: Hedging calamity in Australian sugar, *Journal of Commodity Markets* 21, 100126.

Chalmin, P., 1987, *Traders and merchants: Panorama of international commodity trading*. Taylor & Francis.

Chen, L., Pelger, M., and Zhu, J., 2023, Deep learning in asset pricing, *Management Science* 70, 714-750.
Cheng, I.-H., and Xiong, W., 2014, Why do hedgers trade so much? *Journal of Legal Studies* 43, 183-207.
Cotter, J., Eyiah-Donkor, E., and Potì, V., 2023, Commodity futures return predictability and intertemporal asset pricing, *Journal of Commodity Markets* 31, 100289.
Cotter, J., and Hanly, J., 2010, Time-varying risk aversion: An application to energy hedging, *Energy Economics* 32, 432-441.
Cotter, J., and Hanly, J., 2012, A utility-based approach to energy hedging, *Energy Economics* 34, 817-827.
Diebold, F. X. and Mariano, R. S., 1995, Comparing predictive accuracy, *Journal of Business and Economic Statistics* 13, 253–263.
Ederington, L. H., 1979, The hedging performance of the new futures markets, *Journal of Finance* 34, 157-170.
Fernandez-Perez, A., Frijns, B., Fuertes, A.-M, and Miffre, J., 2018, The skewness of commodity futures returns, *Journal of Banking and Finance* 86, 143-158.
Fischer, T., and Krauss, C., 2018, Deep learning with long short-term memory networks for financial market predictions, *European Journal of Operational Research* 270, 654–669.
Furió, D., and Torró, H., 2020, Optimal hedging under biased energy futures markets, *Energy Economics* 88, 104750.
Gargano, A., and Timmermann, A., 2014, Forecasting commodity price indexes using macroeconomic and financial predictors, *International Journal of Forecasting* 30, 825–843.
Géczy, C., Minton, B., and Schrand, C., 1997, Why firms use currency derivatives? *Journal of Finance* 52, 1323-1354.
Gu, M., Kang, W., Lou, D., and Tang, K., 2023, Relative basis: A better measure of the convenience yield, SSRN Working Paper http://dx.doi.org/10.2139/ssrn.3404561.
Gu, S., Kelly, B., and Xiu, D., 2020, Empirical asset pricing via machine learning, *Review of Financial Studies* 33, 2223–2273.
Guidolin, M., and Pedio, M., 2021, Forecasting commodity futures returns with stepwise regressions: Do commodity-specific factors help? *Annals of Operations Research* 299, 1317–1356
Hollstein, F., Prokopczuk M., Tharann, B., and Wese Simen, C., 2021, Predictability in commodity markets: Evidence from more than a century, *Journal of Commodity Markets* 24, 100171.
Hong, H., and Yogo, M., 2012, What does futures market interest tell us about the macroeconomy and asset prices? *Journal of Financial Economics*, 105, 473-490.
Hurvich, C. M., and Tsai, C.-L., 1989, Regression and time series model selection in small samples, *Biometrika* 76, 297–307.
Jurado, K., Ludvigson, S., and Ng, S., 2015, Measuring uncertainty, *American Economic Review* 105, 1177-1215.
Kang, W., Rouwenhorst, K. G., and Tang, K., 2020, A tale of two premiums: The role of hedgers and speculators in commodity futures markets, *Journal of Finance* 75, 377-417.
Kilian, L., 2009, Not all oil price shocks are alike: Disentangling demand and supply shocks in the crude oil market, *American Economic Review* 99, 1053-1069.
Leland, H., 1998, Agency costs, risk management, and capital structure, *Journal of Finance* 53, 1213-1243.
Marshall, B. R., Nguyen, N. H., and Visaltanachoti, N., 2012, Commodity liquidity measurement and transaction costs, *Review of Financial Studies* 25, 599-638.

McCracken, M. W., and Ng, S., 2016, FRED-MD: A monthly database for macroeconomic research, *Journal of Business and Economic Statistics* 34, 574-589.
McCracken, M. W., and Valente, G., 2018, Asymptotic inference for performance fees and the predictability of asset returns, *Journal of Business and Economic Statistics* 36, 426–437.
Miffre, J., and Rallis, G., 2007, Momentum strategies in commodity futures markets, *Journal of Banking and Finance* 31, 6, 1863-1886.
Neely, C., Rapach, D., Tu, J., and Zhou, G., 2014, Forecasting the equity risk premium: The role of technical indicators, *Management Science* 60, 1772-1791.
Patton, A., Politis, D. N., and White, H., 2009, Correction to automatic block-length selection for the dependent bootstrap, *Econometric Reviews* 28, 372–375.
Pirrong, S.C., 1997, Metallgesellschaft: A prudent hedger ruined, or a wildcatter on NYMEX? *Journal of Futures Markets* 17, 543-578.
Politis, D. N., and Romano, J. P., 1994, The stationary bootstrap, *Journal of the American Statistical Association* 89, 1303–1313.
Rad, H., Low, R., Miffre, J., and Faff, R., 2023, The commodity risk premium and neural networks, *Journal of Empirical Finance* 74, 101433
Rapach, D., Strauss, J., and Zhou, G., 2010, Out-of-sample equity premium prediction: Combination forecasts and links to the real economy, *Review of Financial Studies* 23, 821-862.
Rapach, D., and Zhou, G., 2022, Asset pricing: Time-series predictability, *Oxford Research Encyclopaedia of Economics and Finance.*
Rawls, W., and Smithson, C., 1990, Strategic risk management, *Journal of Applied Corporate Finance* 2, 6-18.
Smith, C., and Stulz, R., 1985, The determinants of firms' hedging policies, *Journal of Financial and Quantitative Analysis* 20, 391-405.
Stoll, H., and Whaley, R., 2010, Commodity index investing and commodity futures prices, *Journal of Applied Finance* 20, 7-46.
Stulz, R., 1984, Optimal hedging policies, *Journal of Financial and Quantitative Analysis* 19, 127-140.
Stulz, R., 1996, Rethinking risk management, *Journal of Applied Corporate Finance* 34, 32-46.
Szymanowska, M., de Roon, F., Nijman, T., and Van Den Goorbergh, R., 2014, An anatomy of commodity futures risk premia, *Journal of Finance* 69, 453-482.
The Economist, 2022, A nickel-hedging fiasco raises three big questions, March 19, 2022.
Wang, Y., Wu, C., and Yang, L., 2015, Hedging with futures: Does anything beat the naïve hedging strategy? *Management Science* 61, 2870-2889.
Wang, S., and Zhang, T., 2024, Predictability of commodity futures returns with machine learning models, *Journal of Futures Markets* 44, 302-322.
Westgaard, S., Fryderberg, S., and Mohanty, S. K., 2022, Fourteen large commodity trading disasters: What happened and what can we learn? *Journal of Commodity Markets* 27, 100221.

Appendix A. Commodity futures return predictors

The table outlines the variables used as predictors for commodity futures returns, along with their data sources and original papers proposing each predictor. LH (SH) denotes the long (short) positions of large hedgers. A positive (negative) hedging pressure indicates net short (long) hedging, associated with backwardation (contango). An asterisk (*) indicates weekly interpolated data from monthly sources, while a double asterisk (**) denotes a two-month lagged variable to account for delays in data publication.

Signal	Definition at the time of portfolio formation t		Data source	References
Panel A: Commodity futures characteristics				
Roll yield	Log price differential between front- and second-nearest contracts	$f_{t,1} - f_{t,2}$	LSEG Datastream	Szymanowska et al. (2014)
Momentum	Front-end log excess returns averaged over the previous year	$\frac{1}{52}\sum_{j=0}^{51} \Delta f_{t-j,1}$	LSEG Datastream	Miffre and Rallis (2007)
Value	Average log front-end futures price over the D days spanning the period 4.5 to 5.5 years before t minus front-end log futures price at time t	$\bar{f}_{t-5yr,1} - f_{t,1}$	LSEG Datastream	Asness et al. (2013)
Hedging pressure	Net short weekly positions of large commercial traders (hedgers) over their total positions averaged over the prior year	$\frac{1}{52}\sum_{j=0}^{51} \frac{SH_{t-j} - LH_{t-j}}{SH_{t-j} + LH_{t-j}}$	CFTC	Basu and Miffre (2013)
Hedgers' net position change	Weekly change in net long position of hedgers, normalized by open interest	$\frac{(LH_t - SH_t) - (LH_{t-1} - SH_{t-1})}{OI_{t-1}}$	CFTC	Kang et al. (2020)
Basis-momentum	Difference in average excess returns between front- and second-nearest contracts over the prior year	$\frac{1}{52}\sum_{j=0}^{51} \Delta f_{t-j,1} - \frac{1}{52}\sum_{j=0}^{51} \Delta f_{t-j,2}$	LSEG Datastream	Boons and Prado (2019)
Skewness	Third moment of the D daily front-end excess returns within the past year	$\frac{1}{D}\frac{\sum_{d=0}^{D-1}(\Delta f_{t-d,1} - \mu_t)^3}{\sigma_t^3}$	LSEG Datastream	Fernandez-Perez et al. (2018)
Relative basis	Difference in front- and second-nearest roll-yields	$(f_{t,1} - f_{t,2}) - (f_{t,2} - f_{t,3})$	LSEG Datastream	Gu et al. (2023)
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	$\frac{1}{W}\sum_{j=0}^{W-1} \frac{\lvert\Delta f_{t-j,1}\rvert}{\$Volume_{t-j}}$	LSEG Datastream	Szymanowska et al. (2014)
Change in open interest	Change in average open interest along the futures curve	$OI_t - OI_{t-1}$	LSEG Datastream	Hong and Yogo (2012)

Appendix A. Commodity futures return predictors (*Cont.*)

Signal	Definition at the time of portfolio formation *t*	Data source	References
Panel B: Financial, macroeconomic and sentiment indicators			
Term spread	Yield difference between 10-year Treasury bonds and 3-month Treasury bills	St. Louis FED	Gargano and Timmermann (2014)
Default spread	Yield difference between Moody's seasoned Baa and Aaa corporate bonds	St. Louis FED	Gargano and Timmermann (2014)
TED spread	Difference between 3-month U.S. LIBOR rate and 3-month U.S. T-bill rate	St. Louis FED	Gargano and Timmermann (2014)
T-bill rate	3-month U.S. Treasury bill rate	St. Louis FED	Gargano and Timmermann (2014)
Bond yield	Long-term U.S. bond yield	St. Louis FED	Hollstein et al. (2021)
Equity return	US market excess return	Prof. Amit Goyal	Hollstein et al. (2021)
Dividend yield	Difference between the log of dividends and the log of lagged prices (*)	Prof. Amit Goyal	Gargano and Timmermann (2014)
Earning price ratio	Difference between the log of earnings and the log of prices (*)	Prof. Amit Goyal	Hollstein et al. (2021)
Industrial production	Log change in U.S. industrial production (*, **)	St. Louis FED	Gargano and Timmermann (2014)
Money supply	Log change in M1 money supply (*, **)	St. Louis FED	Gargano and Timmermann (2014)
Unemployment rate	Number of unemployed as a percentage of the US labor force (*, **)	St. Louis FED	Gargano and Timmermann (2014)
Inflation rate	US consumer price index (all urban consumers) (*, **)	Prof. Amit Goyal	Gargano and Timmermann (2014)
Foreign exchange rates	Log changes in U.S. dollar vs. A.U. dollar, C.A. dollar, N.Z. dollar, S.A. rand, Indian rupee	LSEG Datastream	Gargano and Timmermann (2014)
National activity index	Weighted average of 85 monthly indicators of national economic activity (*, **)	Chicago FED	Cotter et al. (2023)
EPU	Log change in economic policy uncertainty index	Prof. Scott R. Baker	
GPR	Log change geopolitical risk index	Prof. Matteo Iacoviello	
Baltic dry index	Log change in the Baltic dry index: Weighted average freight price	LSEG Datastream	Bakshi et al. (2014)
Real economic activity	(Change) real economic activity index of Kilian (2009) (*, **)	St. Louis FED	Gargano and Timmermann (2014)
Business confidence index	Business's surveys on developments in production, orders and stocks of finished goods in the industry sector (*, **)	OECD	Hollstein et al. (2021)
Consumer confidence index	Households' surveys regarding sentiment on economic and financial situation, unemployment and savings capability (*, **)	OECD	Hollstein et al. (2021)
Sentiment index	Sentiment index of Baker and Wurgler (2006) (*)	Prof. Jeffrey Wurgler	
Uncertainty index	Uncertainty index of Bekaert et al. (2022)	Prof. Nancy Wu	
VIX	CBOE's volatility index	LSEG Datastream	Hollstein et al. (2021)

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 $\Delta\hat{f}_{k,t+1} = \hat{a}_{0,t} + \hat{a}_{1,t} z_{k,t}$, $k = 1, \dots, K$, and $\boldsymbol{\omega}'_t = \left(\frac{1}{K}, \dots, \frac{1}{K}\right)$. We now entertain alternative weighting schemes.

MSE weighting scheme

The MSE weighting scheme is based on forecast accuracy, with higher weights assigned to the forecasts that have lower mean squared error (MSE). The weights are calculated as follows: at each hedge formation time *t*, the past window of $L = 520$ weeks is divided into an estimation window L_0 and an evaluation window L_1 of equal length $\frac{L}{2}$. The first L_0 weeks are used to generate the K out-of-sample univariate forecasts of futures returns for the first week of the evaluation period. The estimation window is then expanded by one week to generate forecasts for the second week of the evaluation period, and so forth. The MSE calculated over the entire evaluation window as $MSE_{k,t} = \sum_{j=1}^{L_1} (\Delta f_{t-j+1} - \Delta\hat{f}_{k,t-j+1})^2 / L_1$ is used to obtain the weights $\omega_{k,t} = \frac{MSE_{k,t}^{-1}}{\sum_{k=1}^{K} MSE_{k,t}^{-1}}$ to construct $E_t(\Delta f_{t+1}|\Omega_t)$. This procedure is repeated at hedge formation time *t*+1, and so forth.

E-Net weighting scheme

The Elastic Net (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: at each hedge formation week *t*, we divide the preceding window of $L = 520$ weeks into an estimation window and an evaluation window ($L_0 = L_1 = \frac{L}{2}$). We repeat the steps of the MSE weighting scheme to obtain the forecasts. Then, we solve the following minimization problem over the evaluation window

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

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

Appendix C. K-Integr (with E-Net regularization) selective hedge

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

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

$$\max_{\boldsymbol{\omega}_t} E_t\left[U\left(\Delta s_{t+1} - (\beta_t - \boldsymbol{\omega}_t{}'\boldsymbol{z}_t)\Delta f_{t+1} - \lambda_{1,t}\sum_{k=1}^{K}\left|\omega_{k,t}\right| - \lambda_{2,t}\sum_{k=1}^{K}\omega_{k,t}^2\right)\middle|\Omega_t\right],$$

subject to the constraint $\sigma\left(\Delta p_{t+1}^{MinVar} - \Delta p_{t+1}^{K-Integr}(\boldsymbol{\omega}_t)\right) \leq \varsigma$, with Δs_{t+1}, Δf_{t+1}, $\Delta p_{t+1}^{K-Integr}$ and Δp_{t+1}^{MinVar} representing the spot, futures, K-Integr and MinVar returns for a given commodity i at time t+1, respectively. β_t is the MinVar hedge ratio of commodity i at time t estimated using L past observations, $\boldsymbol{\omega}_t{}'$ is a $1 \times K$ vector of loadings, $\boldsymbol{z}_t$ is the $K \times 1$ vector of standardized predictors at time t, and $\lambda_{1,t}$ and $\lambda_{2,t}$ are the LASSO and Ridge penalty parameters, respectively, that we set to the same pre-specified value to speed up computation time, i.e., $\lambda_{1,t} = \lambda_{2,t} = \lambda_t$.

The estimation of the K-Integr is as follows. First, the rolling estimation window at hand ($L =$ 520 weeks) is divided into an optimization sample (first 60% weeks of the estimation window) and an evaluation sample (second 40% weeks of the estimation window). Second, the first sample is used to optimize the weights, $\boldsymbol{\omega}_t$, based a pre-specified λ_t, and the expected utility gain of the optimized portfolio is measured over the evaluation sample. This step is repeated for a range of pre-specified λ_t (i.e., twenty evenly-spaced values from 0.0073 to 0.00001). Third, we select the λ_t value that generates the largest expected utility of the optimized portfolio over the evaluation sample. Finally, the selected λ_t is used to find the weights, $\boldsymbol{\omega}_t$, by maximizing the K-Integr (with E-Net) objective function over the entire estimation (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 (black color) and six alternative selective hedge ratios (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.

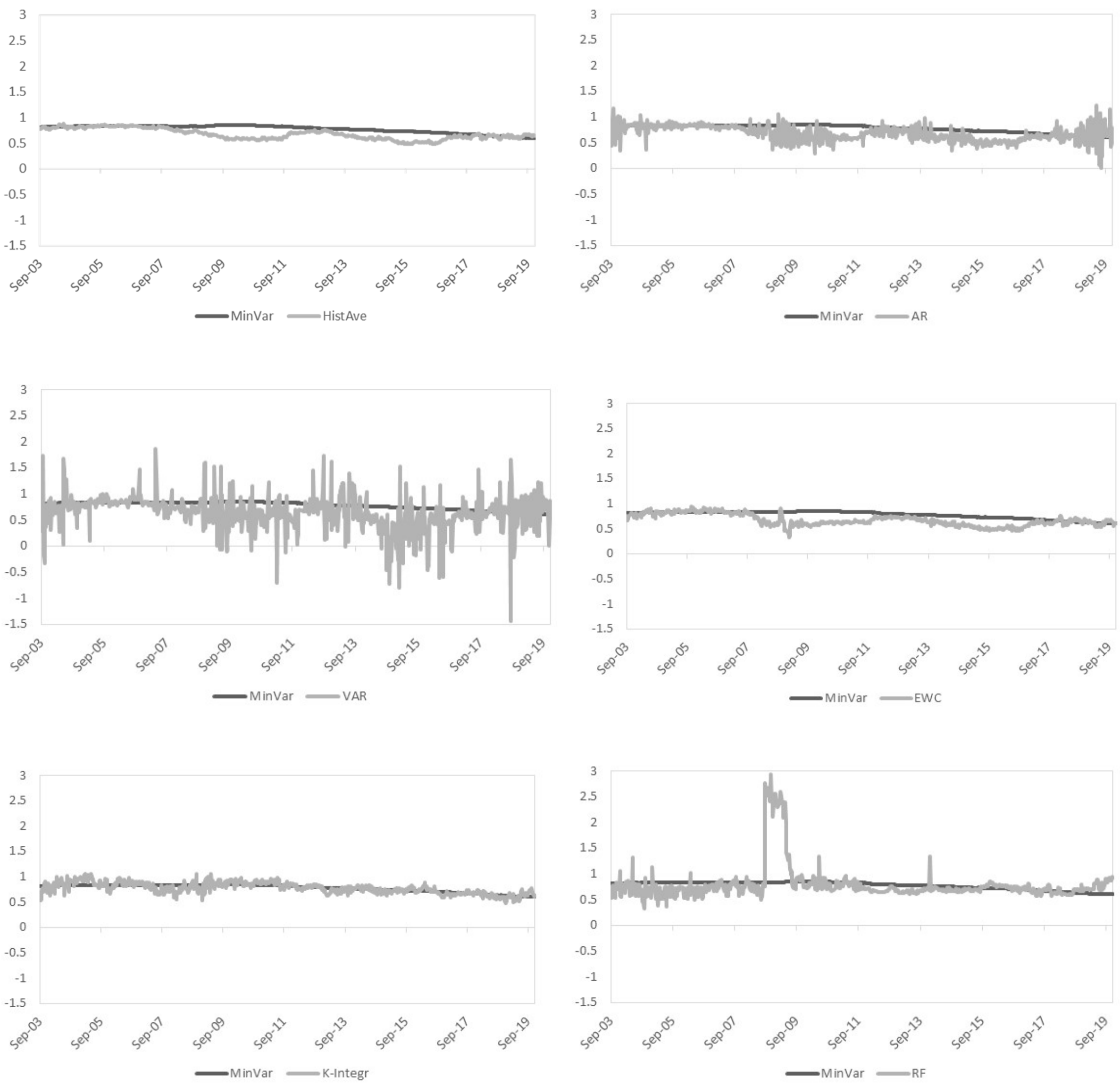

Figure 2. Standard deviation of the hedge ratios

This figure plots the standard deviation of the traditional MinVar hedge ratio alongside six selective hedge ratios for a representative commodity producer, assuming a mean-variance utility and coefficient of relative risk aversion $\gamma = 5$. The reported statistics are averages across commodities.

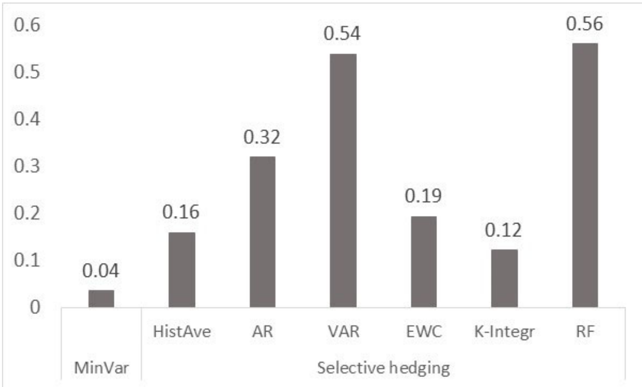

Table 1. Selective hedging strategies

This table lists the selective hedging strategies implemented in the main section of the paper, with variants thereof outlined in the robustness tests section. β_t is the traditional MinVar hedge ratio that minimizes the variance of the hedge portfolio.

Selective hedge ratio	Strategy	Name	References
$h_t = argmax\ U = \beta_t$- $E_t(\Delta f_{t+1}\vert\Omega_t)/\gamma\sigma^2_{f,t}$ $E_t(\Delta f_{t+1}\vert\Omega_t) = \frac{1}{L}\sum_{j=0}^{L-1}\Delta f_{t-j}$	Selective hedge based on recent historical average of futures returns	HistAve	
$h_t = argmax\ U = \beta_t$- $E_t(\Delta f_{t+1}\vert\Omega_t)/\gamma\sigma^2_{f,t}$ $E_t(\Delta f_{t+1}\vert\Omega_t) = \hat{\alpha}_{0,t} + \hat{\alpha}_{1,t}\Delta f_t$	Selective hedge based on AR model forecast	AR(1)	Cotter and Hanley (2010), Cotter and Hanley (2012)
$h_t = argmax\ U = \beta_t$- $E_t(\Delta f_{t+1}\vert\Omega_t)/\gamma\sigma^2_{f,t}$ $E_t(\Delta f_{t+1}\vert\Omega_t) = \hat{\theta}_{0,t} + \hat{\theta}_{1,t}\Delta f_t + \cdots + \hat{\theta}_{p,t}\Delta f_{t-p}$ $+\hat{\varphi}_{1,t}Roll\ yield_t + \cdots + \hat{\varphi}_{p,t}Roll\ yield_{t-p}$ with $Roll\ yield_t$=$f_{t,1} - f_{t,2}$	Selective hedge based on VAR(p) model forecast	VAR(p)	Furió and Torró (2020)
$h_t = argmax\ U = \beta_t$- $E_t(\Delta f_{t+1}\vert\Omega_t)/\gamma\sigma^2_{f,t}$ $E_t(\Delta f_{t+1}\vert\Omega_t) = \boldsymbol{\omega}'_t\widehat{\Delta \boldsymbol{f}}_{t+1}$, $\boldsymbol{\omega}'_t = \left(\frac{1}{K}, \dots, \frac{1}{K}\right)$ with $\widehat{\Delta f}_{k,t+1} = \hat{a}_{0,t} + \hat{a}_{1,t}z_{k,t}$	Selective hedge based on equally-weighted forecast combination	EWC	
$max_{\omega_t}\ U(\beta_t, \boldsymbol{\omega}_t)$ s.t. MinVar tracking error $h_t = \beta_t - \boldsymbol{\omega}'_t\boldsymbol{z}_t$	Selective hedge based on optimized integration of predictors	K-Integr	Barroso et al. (2022)
$h_t = argmax\ U = \beta_t$- $E_t(\Delta f_{t+1}\vert\Omega_t)/\gamma\sigma^2_{f,t}$ $E_t(\Delta \boldsymbol{f}_{t+1}\vert\Omega_t) = g^*(\boldsymbol{Z}_t)$	Selective hedge based on random forest forecasts	RF	

Table 2. Descriptive statistics of spot and futures returns

This table presents summary statistics for the returns of spot and front-end fully-collateralized futures positions, as well as the spot-futures returns correlations. Mean, variance and expected utility are annualized. The utility function is mean-variance with coefficient of relative risk aversion $\gamma = 5.$ Newey-West t-statistics (with truncation lag $[4(T/100)^{2/9}]$ where T is the sample size) for the significance of mean returns are in parentheses and p-values for the significance of correlations are in curly brackets.

	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. Expected utility gain

This table reports the annualized expected utility gains from traditional MinVar and selective hedging strategies based on HistAve, AR, VAR, EWC, K-Integr and RF forecasts. The utility function employed is mean-variance with a coefficient of relative risk aversion $\gamma = 5.$ Positive numbers indicate that hedging the spot position provides greater expected utility to the hedger than not hedging (see Table 2). The numbers in parentheses represent bootstrap p-values for the McCracken and Valente (2018) statistic, with $H_0\colon \Delta E\left(U_{Diff}\right) = \Delta E(U_{SH}) - \Delta E(U_{MinVar}) \leq 0$ versus $H_1\colon \Delta E\left(U_{Diff}\right) > 0$, where $\Delta E(U)$ is the expected utility gain as defined in Equation (4), and SH refers to the selective hedging strategy being analyzed. Panel E summarizes the average expected utility gains across commodities both before and after transaction costs (TC) of 8.6 basis points (Marshall et al., 2012). The sample period for each commodity is detailed in Table 2.

	MinVar	Selective hedges											
		HistAve		AR		VAR		EWC		K-Integr		RF	
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)
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)
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)
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)
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)
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)
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)
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)
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)
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)
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)
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)
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)
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)
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)
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)
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)
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)
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)
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)
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)
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)
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)
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)
Panel E: All commodities													
Before TC	0.1627	0.1573		0.1331		0.0922		0.1572		0.1661		0.0728	
After TC	0.1622	0.1564		0.1227		0.0760		0.1553		0.1629		0.0677	

Table 4. Statistical forecast accuracy

This table reports the R^2_{OOS} statistic that assesses the accuracy of the forecasts underlying a given selective hedge relative to the zero-return forecast underlying the MinVar hedge. A negative or zero R^2_{OOS} value suggests that the futures return forecast at hand is not more accurate than the zero-return forecast. *p*-values of the Diebold and Mariano (1995) test are shown in parentheses. The sample period for each commodity is detailed in Table 2.

	HistAve		AR		VAR		EWC		K-Integr		RF	
Panel A: Agriculture												
Cocoa	-0.32%	(0.95)	-0.52%	(0.98)	-1.32%	(1.00)	-0.46%	(0.98)	0.05%	(0.37)	-0.87%	(0.84)
Coffee	-0.34%	(0.97)	-1.14%	(0.99)	-1.66%	(0.97)	-0.25%	(0.91)	0.16%	(0.11)	-0.69%	(0.87)
Corn	-0.31%	(0.90)	-0.72%	(0.89)	-0.93%	(0.89)	-0.38%	(0.91)	-0.01%	(0.54)	0.72%	(0.38)
Cotton	-0.45%	(0.93)	-0.85%	(0.99)	-2.07%	(1.00)	-0.46%	(0.89)	0.03%	(0.42)	-0.53%	(0.75)
Frozen orange juice	-0.32%	(0.99)	-0.66%	(0.91)	-1.76%	(0.98)	-0.35%	(0.97)	-0.09%	(0.81)	-0.23%	(0.81)
Soybeans	-0.06%	(0.57)	-0.35%	(0.74)	-0.97%	(0.89)	-0.13%	(0.63)	0.13%	(0.15)	-0.35%	(0.75)
Soybeans meal	0.06%	(0.46)	-0.73%	(0.81)	-2.13%	(0.98)	0.08%	(0.45)	0.17%	(0.12)	-0.89%	(0.85)
Soybeans oil	-0.24%	(0.91)	-0.48%	(0.94)	-0.36%	(0.75)	-0.32%	(0.92)	0.08%	(0.26)	0.11%	(0.58)
Sugar	-0.23%	(0.85)	-0.54%	(0.91)	-0.81%	(0.95)	-0.24%	(0.85)	0.20%	(0.10)	-0.70%	(0.91)
Wheat	-0.20%	(0.76)	-0.66%	(0.92)	-1.22%	(0.97)	-0.17%	(0.72)	-0.04%	(0.63)	-0.50%	(0.72)
Panel B: Energy												
Crude oil	-0.30%	(0.72)	-0.76%	(0.85)	-2.52%	(0.99)	0.08%	(0.43)	0.07%	(0.31)	0.70%	(0.31)
Gasoline RBOB	-0.53%	(0.71)	2.61%	(0.05)	-1.22%	(0.62)	-0.88%	(0.79)	-1.04%	(0.70)	0.09%	(0.43)
Heating oil	-0.29%	(0.71)	-0.56%	(0.77)	-1.26%	(0.92)	0.04%	(0.46)	0.12%	(0.20)	0.71%	(0.34)
Natural gas	0.45%	(0.20)	0.08%	(0.45)	-1.95%	(0.95)	0.63%	(0.14)	0.09%	(0.26)	0.62%	(0.15)
Unleaded gas	0.88%	(0.27)	0.50%	(0.39)	-0.93%	(0.67)	0.92%	(0.27)	0.02%	(0.47)	0.70%	(0.08)
Panel C: Livestock												
Feeder cattle	-0.19%	(0.64)	-0.49%	(0.66)	-1.02%	(0.80)	-0.15%	(0.61)	0.11%	(0.26)	-2.37%	(0.96)
Lean hogs	0.00%	(0.50)	0.21%	(0.33)	-0.47%	(0.78)	0.05%	(0.45)	0.24%	(0.18)	0.50%	(0.59)
Live cattle	-0.36%	(0.89)	-0.98%	(0.89)	-0.76%	(0.84)	-0.35%	(0.86)	0.24%	(0.03)	-0.76%	(0.91)
Panel D: Metal												
Copper	-0.32%	(0.72)	-0.68%	(0.87)	-0.69%	(0.82)	-0.10%	(0.57)	0.08%	(0.26)	-0.20%	(0.64)
Gold	-0.12%	(0.59)	-0.39%	(0.74)	-1.42%	(0.98)	-0.28%	(0.69)	-0.21%	(0.95)	-3.53%	(0.97)
Lumber	-0.16%	(0.64)	-0.37%	(0.78)	-0.09%	(0.57)	-0.17%	(0.64)	0.16%	(0.11)	0.31%	(0.36)
Palladium	0.00%	(0.51)	0.08%	(0.40)	-1.58%	(0.99)	0.06%	(0.43)	0.20%	(0.19)	-1.03%	(0.91)
Platinum	-0.23%	(0.63)	-0.79%	(0.80)	-1.81%	(0.96)	-0.16%	(0.60)	-0.13%	(0.72)	-1.04%	(0.78)
Silver	-0.27%	(0.77)	-0.82%	(0.95)	-1.30%	(0.97)	-0.36%	(0.83)	-0.06%	(0.68)	-1.09%	(0.93)

Table 5. Abnormal return of the selective hedges

This table reports the abnormal return of selective hedging measured as the (annualized) intercept or alpha of a spanning regression of the selective hedge portfolio returns on the returns of the MinVar hedge portfolio. Newey-West t-statistics (with truncation lag $[4(T/100)^{2/9}]$ where T is the rolling estimation window length) for the significance of abnormal returns are in parentheses. The sample period for each commodity is 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)

Table 6. Risk of the hedge portfolios

This table reports the annualized variance of the traditional MinVar and selective hedge portfolios. The p-values of the Diebold and Mariano (1995) test for $H_0: E\left[(\Delta p_t^{SH})^2 - (\Delta p_t^{MinVar})^2\right] \leq 0$ versus $H_1: E\left[(\Delta p_t^{SH})^2 - (\Delta p_t^{MinVar})^2\right] > 0$ are shown in parentheses. The sample period for each commodity is detailed in Table 2.

	MinVar	Selective hedges											
		HistAve		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)
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)
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)
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)
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)
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)
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)
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)
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)
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)
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)
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)
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)
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)
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)
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)
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)
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)
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)
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)
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)
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)
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)
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)

Table 7. Alternative specifications of the traditional hedge ratios

The table reports the annualized expected utility gain of various traditional hedges and their selective hedge counterparts. The traditional hedges are defined through the OLS regression model (referred to in the rest of the paper as MinVar hedge ratio), the naïve one-to-one ratio, VAR(1,1), VEC(1,1), bivariate BEKK-GARCH(1,1), DCC-GARCH(1,1) and Markov regime-switching OLS regression model. The reported statistics are averages across commodities.

	Traditional hedge	Selective hedges					
		HistAve	AR	VAR	EWC	K-Integr	RF
MinVar	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 8. Alternative specifications of the selective hedge ratios

This table reports annualized expected utility gains from selective hedging strategies: EWC (Panel A), K-Integr (Panel B), ML (Panel C), and miscellaneous (Panel D). The first column of Panels A to C corresponds to the baseline in Table 3. 'K=10' refers to 10 commodity-specific predictors, while 'K=3' denotes 3 predictors (roll yield, momentum, and value). In Panel A, MSE and E-Net use the inverse of mean squared errors or elastic net weights (see Appendix B). PC1 (PC1-2) utilizes the first (two) principal components of the information variables. In Panel B, K-Integr E-Net includes an elastic-net penalty for overfitting (see Appendix C), ς is the tracking error threshold, and Pooled K-Integr is based on pooled data across commodities. In Panel C, DNN stands for deep neural networks with specified hidden layers, and LSTM refers to long-short term memory networks with indicated units. Panel D includes Comb, which uses equal-weighted combinations of predictions from the six selective hedging models in Table 3, CS employs Fama-MacBeth cross-sectional forecasts, and Naïve Basis uses the roll yield at time t as a futures return forecast. Expected utility gains are averages across commodities.

Panel A: EWC and its variants								
Baseline	K=10	K=3	MSE	E-Net	PC1	PC1-2		
0.1572	0.1534	0.1430	0.1568	0.1328	0.0993	0.0785		
Panel B: K-Integr and its variants								
Baseline	K=10	K=3	E-Net	ς = 5%	ς = 10%	Pooled		
0.1661	0.1608	0.1608	0.1643	0.1658	0.1351	0.1663		
Panel C: Machine learning variants								
Baseline	K=10	K=3	DNN2	DNN3	LSTM4-DNN2	LSTM4-DNN3	LSTM8-DNN2	LSTM8-DNN3
0.0728	0.1529	0.1388	0.0231	0.1039	0.1436	0.1107	0.1508	0.1326
Panel D: Miscellaneous models								
Comb	CS (K=10)	CS (K=3)	Naïve Basis					
0.1630	0.1335	0.1456	0.0465					

Table 9. Subsample analysis

The table presents the annualized expected utility gains of hedging strategies deployed in various subsample periods: pre- and post-financialization of commodities (using the January 2006 cutoff suggested by Stoll and Whaley, 2010), backwardation and contango phases, NBER expansions and recessions, high versus low commodity market volatility (defined using a GARCH model fitted to weekly spot returns), and high versus low macroeconomic uncertainty (based on the macroeconomic uncertainty index from Jurado et al., 2015). The subsamples are determined ex-post. The reported expected utility gains represent averages across commodities.

	MinVar	Selective hedges					
		HistAve	AR	VAR	EWC	K-Integr	RF
Financialization							
Pre	0.0825	0.0958	0.0494	0.0328	0.0898	0.0878	0.1088
Post	0.1922	0.1797	0.1528	0.1116	0.1807	0.1948	0.0758
Backwardation and contango phases							
Backwardation	-0.0085	0.0024	-0.0229	-0.1303	0.0009	-0.0069	-0.0909
Contango	0.2473	0.2276	0.2139	0.1858	0.2284	0.2502	0.1539
NBER business cycle							
Expansion	0.1311	0.1310	0.1113	0.0801	0.1297	0.1342	0.1276
Recession	0.4808	0.4206	0.3469	0.2118	0.4322	0.4878	-0.4446
Spot volatility							
Low	0.0748	0.0826	0.0794	0.0545	0.0841	0.0767	0.0638
High	0.2506	0.2320	0.1869	0.1296	0.2303	0.2554	0.0818
Macro uncertainty index							
Low	0.0829	0.0893	0.0655	0.0328	0.0895	0.0901	0.0866
High	0.2346	0.2229	0.2140	0.1603	0.2227	0.2380	0.0792

Table 10. Risk aversion, estimation window, rebalancing, maturities and long hedging

This table presents the annualized expected utility gains for various hedging strategies, accounting for time-varying risk aversion, using expanding windows, with monthly or quarterly rebalancing, for different futures maturities ranging from the second (F2) to the sixth (F6) contract along the curve, and for a long hedger. The first row provides the baseline results from Table 3. Unless otherwise specified, the coefficient of relative risk aversion is set to 5. The reported expected utility gains are averages across commodities

		MinVar	Selective hedges					
			HistAve	AR	VAR	EWC	K-Integr	RF
Baseline		0.1627	0.1573	0.1331	0.0922	0.1572	0.1661	0.0728
Time-varying risk aversion		0.0941	0.0858	0.0470	-0.0171	0.0854	0.0983	0.0601
Expanding windows		0.1609	0.1617	0.1321	0.1113	0.1593	0.1632	0.0471
Monthly rebalancing		0.1984	0.1869	0.1708	0.1124	0.1840	0.1819	0.1093
Quarterly rebalancing		0.1975	0.1985	0.1973	0.1668	0.1982	0.1887	0.1604
Maturity	F2	0.1573	0.1520	0.1303	0.0920	0.1525	0.1603	0.0205
	F3	0.1484	0.1427	0.1218	0.0913	0.1440	0.1514	-0.0087
	F4	0.1260	0.1236	0.1058	0.0705	0.1260	0.1289	0.0493
	F5	0.1334	0.1289	0.1046	0.0609	0.1318	0.1361	-0.1381
	F6	0.1223	0.1242	0.1026	0.0712	0.1253	0.1258	-0.0395
Long hedging		0.1172	0.1088	0.0839	0.0409	0.1085	0.1197	0.0215