# Does Speculation in Futures Markets Improve Commodity Hedging Decisions?

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

**Abstract**

This article performs a comparative analysis of traditional and selective hedging strategies in commodity futures markets. Traditional hedging is aimed solely at reducing the risk of the commodity spot positions, whereas selective hedging additionally pursues economic gains by engaging in speculation based on the hedger's prediction of the commodity futures return. We construct selective hedges using diverse forecasting approaches that range from the naïve historical average to more sophisticated techniques such as machine learning. The hedging strategies are assessed through the lens of hedging effectiveness based on the expected mean-variance utility of the hedged returns. Out-of-sample results for 24 commodities endorse traditional over selective hedging, as the latter increases risk but fails to generate additional returns. The findings survive various reformulations of the hedges, longer estimation windows, and alternative rebalancing frequencies, inter alia.

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[†] University College Dublin, Ireland; e-mail: adrian.fernandez-perez@ucd.ie.

[‡] Bayes Business School, England; e-mail: a.fuertes@city.ac.uk.

[§] Audencia Business School, France, e-mail: jmiffre@audencia.com

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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 naïve selective hedge where the futures return prediction is the historical average return. Next, we consider selective hedges that employ futures return forecasts derived from either an autoregressive model (Cotter and Hanly, 2010, 2012), a vector autoregressive model (Furió and Torró, 2020), a combination of univariate regression forecasts (Rapach et al., 2010) or style integration (inspired by Brandt et al., 2009; Barroso et al., 2022). Lastly, we design selective hedges that use state-of-the-art machine learning methods to accommodate any form of nonlinearity between the target commodity futures return and the predictors (Fischer and Krauss, 2018; Gu et al., 2020; Chen et al., 2023). To the best of our knowledge, the selective hedges based on historical average returns, the combination of univariate regression forecasts, and machine learning forecasts are new to the literature on risk management. By entertaining a wide range of predictive methods for the commodity futures return, our objective is to provide the selective hedging framework with ample opportunities to succeed.

We implement the hedges on 24 commodities spanning various sectors (agriculture, energy, livestock, and metals). The effectiveness of the various 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 analysis suggests that traditional hedging is not statistically surpassed by selective hedging in terms of the expected utility gain afforded to the commodity hedger. Thus, commodity hedgers are for the most part better off by assuming no change in the futures price over the hedging horizon. The inability of selective hedging to consistently and significantly outperform traditional hedging in practice reflects the low out-of-sample time-series predictability of individual commodity futures returns. Thus, the speculative component worsens the risk coverage aspect without generating any extra return. This outcome is exacerbated by transaction costs. Various robustness tests confirm that the effectiveness of traditional hedging is not challenged when we re-design the traditional and selective hedge ratios, incorporate time-varying risk aversion, evaluate the utility gains over sub-samples, consider longer estimation windows to obtain the forecasts, deploy long and short hedging, allow for different rebalancing frequencies, use longer-dated futures contracts as hedging instruments or study the hedging problem of a diversified commodity producer.

The main takeaway from our analysis is that, although selective hedging stems as the optimal solution of theoretical models of hedging, it is challenging for commodity firms to benefit (i.e., obtain a higher utility) from this practice relative to the traditional hedging method. The strong recommendation that arises from this study is that risk managers are generally better off hedging spot price risk without incorporating their market views into their hedging program.

The present paper 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 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]

Our article also 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 their evidence to other predictors and agricultural commodity returns. Both papers argue that the observed predictability is consistent with conditional pricing models. The evidence on out-of-sample commodity return predictability is far less conclusive. Hollstein et al. (2021) argue that business cycle and commodity characteristics can predict individual commodity returns. Ahmed and Tsvetanov (2016) and Guidolin and Pedio (2021) contend instead that individual commodity return predictability is at best very low and Wang and Zhang (2024) find very mixed evidence from machine learning methods. Adopting a zero-return

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

[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).

(no-predictability) expectation as benchmark, which is the appropriate benchmark in the present study as it is the assumption implicit in traditional hedging, we confirm that there is weak out-of-sample predictability in individual commodity futures returns.

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, $\Delta s_{t+1}$ is the spot return, $\Delta f_{t+1}$ is the futures return, $h_t$ is the optimal hedge ratio that defines the number of short futures positions per unit of output or spot position, and the parameter $\gamma$ 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 $\Omega_t$, 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 $\Omega_t$.

The selective hedge is made up of a minimum-variance component, $\beta_t$, 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 $\beta_t$ as the OLS slope coefficient of a regression of spot returns on futures returns (Ederington, 1979) which we refer to as MinVar hedge. Other estimation approaches for the traditional hedge ratio are considered in the robustness section.

*2.2. Competing selective hedging strategies*

Selective hedging requires a forecast of the futures return as formalized in Equation (2). A simple forecast is the historical average (HistAve) of the futures return, $E_t(\Delta f_{t+1}|\Omega_t) = \frac{1}{L}\sum_{j=0}^{L-1}\Delta f_{t-j}$, which arises from the assumption that the futures price follows a random walk with drift. To the best of our knowledge, this selective hedge has not been considered in prior studies. As Cotter and Hanly (2010, 2012), we deploy the autoregressive (AR) selective hedge based on the forecast $E_t(\Delta f_{t+1}|\Omega_\mathrm{t}) = \hat{\alpha}_{0,t} + \hat{\alpha}_{1,t}\Delta f_t$ where $\hat{\alpha}_{0,t}$ and $\hat{\alpha}_{1,t}$ are estimated at time *t* using the futures return history $\{\Delta f_{t-j}\}_{j=0}^{L-1}$. As in Furió and Torró (2020), we extend the latter to the vector autoregressive (VAR) selective hedge which hinges on a futures return forecast derived from a bivariate VAR(*p*) model fitted to past futures returns and roll-yield data.[3] These three selective hedges exploit a very limited information set $\Omega_t$.

Next, we implement selective hedges that rely on an information set $\Omega_t$ with $K = 37$ predictors. A novel selective hedge is based on the equal-weight combination (EWC) of univariate regression forecasts advocated, for instance, by Rapach et al. (2010) and Hollstein et al. (2021) for equities and commodities, respectively. Specifically, the futures return forecast is constructed as $E_t(\Delta f_{t+1}|\Omega_\mathrm{t}) = \boldsymbol{\omega}_t'\Delta\hat{\boldsymbol{f}}_{t+1}$where $\boldsymbol{\omega}_t' = \left(\frac{1}{K}, \dots, \frac{1}{K}\right)$ with $\Delta\hat{f}_{k,t+1} = \hat{\alpha}_{0,t} + \hat{\alpha}_{1,t}z_{k,t}$, denoting each of the forecasts conditioned upon each of the predictors in the available set $\boldsymbol{z}_t = \left(z_{1,t}, z_{2,t}, \dots, z_{K,t}\right)'$.

Inspired by the optimal currency overlay strategy of Barroso et al. (2022), we also deploy a selective hedge that builds on the cross-sectional style-integration literature initiated by Brandt et al. (2009) where multiple asset characteristics proxy for expected returns. Instead, our hedger is assumed to integrate time series predictors solving the problem,

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

with $\Delta s_{t+1}$, $\Delta f_{t+1}$, and $\Delta p_{t+1}^{K-Integr}$ denoting the spot, futures and K-Integr hedge returns for a given commodity *i* at time *t*+1, $\beta_t$ is the MinVar hedge ratio of commodity *i* at time *t*, $\boldsymbol{\omega}_t$ is a $K \times 1$ vector of loadings estimated at time *t*, and $\boldsymbol{z}_t = \left(z_{1,t}, z_{2,t}, \dots, z_{K,t}\right)'$ is a $K \times 1$ vector of standardized predictors with zero mean and unit deviation at time *t*. To ensure that the K-Integr portfolio does not depart too much from the benchmark MinVar portfolio, we restrict the optimization with the tracking error constraint $\sigma\left(\Delta p_{t+1}^{MinVar} - \Delta p_{t+1}^{K-Integr}(\boldsymbol{\omega}_t)\right) \leq \varsigma$ where $\sigma(\cdot)$

[3] The rationale for extending the AR model to a bivariate VAR model is that by reflecting commodity inventory levels, the roll-yield can predict futures returns.

denotes the standard deviation, $\Delta p_{t+1}^{MinVar}$ is the traditional MinVar hedge return and $\varsigma$ is a tracking error threshold. As with all other hedges, a window of past $L$-observations is used to construct the K-Integr hedge at each time $t$. The K-Integr selective hedge has not been studied yet in the context of commodity hedging.

Lastly, by allowing for complex nonlinear relationships between candidate predictors and target futures returns, machine learning (ML) methods can be a fruitful approach to construct selective hedges. The ML forecast of the futures return is constructed as $E_t(\Delta \boldsymbol{f}_{t+1}|\Omega_t) = g^*(\boldsymbol{z_t})$ where $\Delta \boldsymbol{f}_{t+1}$ is a $1 \times N$ vector of futures returns at time $t$+1 pooled across commodities, $\boldsymbol{z}_t$ is the $K \times N$ vector of standardized predictors at time $t$, and $g^*(\cdot)$ is the nonlinear function implicit in the ML method at hand. Following the literature on machine learning (Fischer and Krauss, 2018; Gu et al., 2020; Chen et al., 2023; Rad et al., 2023), the nonlinear function $g^*(\cdot)$ is operationalized through a supervised ML algorithm such as random forests (RF), in the main analysis, and deep neural networks (DNN), deployed as such or in conjunction with long-short term memory (LSTM) units, in the robustness section. To our best knowledge, the machine learning selective hedges are new to the literature. Table 1 lists the selective hedges in the main empirical section of the paper.

[Insert Table 1 around here]

### *2.3. Hedging effectiveness*

We compare the hedging strategies according to their hedging *effectiveness* defined as the expected utility of the hedge portfolio versus the expected utility of the unhedged spot position (utility gain),

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

where $U(\cdot)$ is the mean-variance utility function in Equation (1). Unlike other portfolio performance metrics such as the Sharpe ratio, the expected utility gain is a consistent measure of hedging effectiveness because it allows us to embed the same level of risk aversion $\gamma$ in the hedge ratio construction, Equation (2), as in the hedge performance evaluation, Equation (4). In the main analysis, we employ the constant coefficient of relative risk aversion $\gamma = 5$, while time-varying values are considered in the robustness tests.

In order to provide statistical significance to the differential in hedging effectiveness (selective versus MinVar strategy), we deploy the McCracken and Valente (2018) test with null hypothesis $H_0\colon \Delta E(U_{Diff}) = \Delta E(U_{SH}) - \Delta E(U_{MinVar}) \leq 0$ and alternative hypothesis $H_1\colon \Delta E(U_{Diff}) > 0$ where $\Delta E(U)$ is the expected utility gain as defined in Equation (4) and the subscript $SH$ denotes the selective hedging strategy at hand. The inference is based on the stationary bootstrap 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, $\{\Delta s_{t,b}\}_{t=1}^{T}$, $\{\Delta f_{t,b}\}_{t=1}^{T}$, $\{\boldsymbol{z}_{t,b}\}_{t=1}^{T}$, where $b = 1, \ldots, B$ denotes each replication. The demeaned empirical distribution $\{\Delta U^{*}_{Diff,b}\}_{b=1}^{B}$ facilitates the bootstrap *p*-value for the test statistic.

## 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 Refinitiv 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 measured as weekly log futures price changes plus the risk-free rate, $\Delta f_{t+1} = (f_{t+1,T} - f_{t,T}) + r_{F,t+1}$ with $f_{t,T}$ denoting the week *t* log price of the futures contract with maturity $T$ and $r_{F,t+1}$ the 1-month U.S. Treasury bill rate as proxy for the risk free rate. We create continuous futures return series using the prices of front-end contracts except in maturity months when we roll to the second-nearest contracts following the standard approach in the empirical commodity futures literature (e.g., Szymanowska et al., 2014; Boons and Prado, 2019). The summary statistics for commodity 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]

In addition, we consider $K = 37$ variables as predictors of individual commodity futures returns in the EWC, K-Integr and machine learning selective hedges. All the variables are sampled at the weekly frequency and can be classified in two groups. The first group comprises the 10 commodity futures characteristics argued previously to price commodity futures either in the time series or in the cross section. The second group includes 27 financial, macroeconomic and sentiment indicators that can proxy the general state of the economy and thus capture financing costs and short-term mismatches between the demand and supply of commodities. Appendix A provides a detailed description of each of the 37 predictors, presents the data sources, as well as the main references.

## 4. Main Empirical Results

### *4.1. Commodity hedge ratios*

The hedging strategies are deployed sequentially out-of-sample (OOS) to mimic the hedging decisions of a representative single-commodity producer in real time. Specifically, at each sample week *t,* the covariance, $\sigma_{sf,t}$, variance, $\sigma_{f,t}^2$, and 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 then held from week *t* to week *t*+1. The estimation window is then rolled forward by one week to construct a new hedge portfolio at week *t*+1 and so forth.

In the main analysis, we assume a weekly rebalancing frequency, rolling estimation windows of $L$ = 520 weeks, and a coefficient of relative risk aversion $\gamma$ = 5. For the VAR($p$) selective hedge, the appropriate lag order $p$ (setting the maximum at 12) is identified each week using a rolling window of $L$ observations and the Akaike Information Criteria (AIC) as in Furió and Torró (2020). For the K-Integr selective hedge, we adopt the tracking error threshold $\varsigma = 2\%$ p.a. as in Barroso et al. (2022). The RF forecasts are obtained as follows (see Gu et al., 2020). First, we split the sample into training (the initial 60% of the $L$-length estimation window) and validation (the most recent 40% of the estimation window). We pool the information on the $K$ predictors and target futures returns across commodities for each (training and validation) sample. Second, we optimize the RF over the training sample upon various hyperparameter values[4] and compute the mean squared error (MSE) over the validation sample as measure of fit of the trained RF. Third, the values of the hyperparameters that deliver the lowest MSE over the validation sample are used to optimize the RF over the entire (training and validation) estimation sample, and ultimately, to forecast the futures return using the optimized vector of predictors. The RF is optimized once a year, that is, the first optimization is carried out on the last week of September 2013 using the first $L = 520$-week estimation window, the next optimization on the last week of September 2014 and so on.

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

[4] The number of iterations or trees, $S$, is set to 300. The hyperparameter values considered are the number of randomly chosen predictors in each simulation, $R = \{3, 5, 10, 20, 30\}$, and the maximum number of branches or depth of the tree, $D = \{1, 2, 3, 4, 5, 6\}$.

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 latter is not surprising given the stringent tracking error constraint of the K-Integr hedge relative to the MinVar hedge. More volatile hedge ratios will be naturally penalized by higher rebalancing costs.

[Insert Figures 1 and 2 around here]

*4.2. Hedging effectiveness*

Table 3 presents the hedging effectiveness or the expected utility gain of the various hedges for each of the 24 commodities obtained from Equation (4). As Table 3, Panel E, shows, the expected utility gain of the MinVar and K-Integr hedges are the largest at 16.27% p.a. and 16.61% p.a., respectively, on average across commodities. The K-Integr hedge, which bestows the higher utility gains to 19 commodities (out of 24) than the MinVar hedge, is the closest competitor to MinVar. The HistAve, EWC, AR, VAR and RF hedges are less effective with expected utility gains of 15.73%, 15.72%, and 13.31%, 9.22% and 7.28% p.a., respectively, on average.

[Insert Table 3 around here]

Table 3 also reports the *p*-values of the McCracken and Valente (2018) test for the difference in expected utility gains between selective and traditional hedging. The *p*-values are generally large which indicates that the expected utility gain of selective hedging is not superior to that of MinVar. Thus, there is a lack of evidence to abandon traditional hedging in favor of selective hedging: none of the selective hedges delivers strong and consistent outperformance relative to the benchmark at the 5% level. Given besides its simplicity, it seems reasonable to recommend traditional hedging.

We bring transaction costs into the analysis by computing 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 8.6 basis point transaction cost (TC) estimate of Marshall et al. (2012). We then calculate the net expected utility gain of each strategy using Equation (4). Table 3, Panel E, presents the results across commodities. Transaction costs have a minimal impact on the expected utility gain of the MinVar hedge (utility gain reduction of 0.05% p.a.) and 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. Hence, the consideration of transaction costs reinforces our earlier finding.

*4.3. Understanding the effectiveness of traditional hedging*

Next, we seek to explain why selective hedging does not significantly increase expected utility of hedging. First, we adopt the $R^2_{OOS}$ measure of Campbell and Thompsom (2008) to gauge statistical forecasts accuracy (under a mean squared error loss function)

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

where $\widehat{\Delta f}^{MinVar}_{t+1} = 0$ is in the present context the no-predictability (zero expected commodity futures return) assumption that underlies the traditional hedging strategy, and $\widehat{\Delta f}^{SH}_{t+1}$ is the forecast used to determine the speculative component in Equation (2) and form the selective hedge.[5] $R^2_{OOS} \leq 0$ reveals that the forecasts are no more accurate than the benchmark, and $R^2_{OOS} > 0$ that they are more accurate. We provide statistical significance to the findings with the Diebold and Mariano (1995) test for the null hypothesis $H_0\colon E(d_t) \leq 0$ versus the alternative $H_1\colon E(d_t) > 0$ where $d_t =$

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

$\Delta f_{t+1}^2 - \left(\Delta f_{t+1} - \widehat{\Delta f}_{t+1}^{SH}\right)^2$ is the squared error differential. The evidence in Table 4 suggests scant predictability, namely, the commodity futures return forecasts used as inputs in the selective hedges are not more accurate than the zero expected return that underlies the MinVar hedge.

[Insert Table 4 around here]

Does selective hedging accrue any additional return versus traditional hedging? To address this question, we estimate spanning regressions of the selective hedge portfolio returns on the MinVar hedge portfolio returns. The regression intercept or alpha is a measure of the additional return that is captured when incorporating the hedger's view of the commodity futures market into the hedging program. Table 5 presents the annualized alpha alongside the robust Newey-West adjusted *t*-statistics. With 20 positive alphas, we note the relative success of the K-Integr hedge. Yet, the ability of selective hedging to generate positive and statistically significant alpha remains negligible, namely, selective hedging does not capture additional returns versus traditional hedging.

[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. To provide statistical significance to the findings, we follow Wang et al. (2015) and deploy the Diebold and Mariano (1995) test for the null hypothesis $H_0: E\left[(\Delta p_t^{SH})^2 - (\Delta p_t^{MinVar})^2\right] \leq 0$ versus the alternative $H_1: E\left[(\Delta p_t^{SH})^2 - (\Delta p_t^{MinVar})^2\right] > 0$ with $(\Delta p_t^{SH})^2$ and $(\Delta p_t^{MinVar})^2$ denoting the squared returns of the selective and traditional hedge portfolios, respectively.

Table 6 presents the annualized hedge portfolio variances and the *p*-values of the Diebold and Mariano (1995) test. With a variance of 3.37% p.a. on average across commodities, the MinVar hedge portfolio stands out as the least volatile which suggests that traditional hedging provides the best risk coverage. By contrast, the risk reduction achieved by selective hedging is not more appealing as borne by selective hedge portfolio variances which range from 3.45% (K-Integr hedge) to 8.46% (RF hedge) p.a. on average across commodities.[6] The small $p$-values of the Diebold and Mariano (1995) test suggest that selective hedging significantly increases risk relative to traditional hedging. Thus, the primary goal of covering the risk of the spot position is undermined by selective hedging. Hence, both effects – the failure to improve the expected return and the larger variance – render selective hedging portfolios unappealing versus traditional hedging.

[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).[7]

Overall, although selective hedging is the optimal solution of theoretical models of hedging, it is challenging to make it worthwhile in practice because it requires the hedger to construct a commodity futures return forecast that is more accurate than the zero-return expectation that

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[6] We additionally assessed the downside risk of the various hedge portfolios using the maximum drawdown and Gaussian 1% VaR measures. MinVar obtains the lowest maximum drawdown (11.67%) and the highest 1% VaR (-4.78%) as averaged across commodities. The corresponding measures for the selective hedges range from 11.92% to 22.11% for maximum drawdown and from -8.75% to -4.90% for VaR. The results therefore indicate that traditional hedging provides the best spot risk protection to the commodity producing firm also in terms of downside risk.

[7] 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.

underlies the traditional hedging strategy. Selective hedging does not routinely provide additional utility to the commodity producer because its inferior risk coverage does not come accompanied by an increase in expected return. On the basis of this evidence, we assert that commodity producers are often better off by adhering to the simpler traditional hedging practice that rules out speculation.

## 5. Robustness Tests

In this section, we alter various aspects of the main empirical analysis to re-examine the effectiveness of selective hedging vis-à-vis traditional hedging. Only one feature of the baseline models is changed at a time, keeping all other features constant. In the interest of space, we report results on average across commodities with the disaggregated results available upon request.

### 5.1. *Alternative designs of the traditional hedge ratio*

As articulated in the theoretical framework of Anderson and Danthine (1981), the first component $\beta_t$ of the mean-variance utility-maximizing hedge ratio, Equation (2), is the minimum-variance hedge ratio which is a function of two (co)variance parameters, $\sigma_{sf,t}$ and $\sigma_{f,t}^2$. Since Ederington (1979)'s seminal paper, the linear OLS regression has been widely used to consistently estimate $\beta_t$; this is the traditional hedge ratio that we used in the main analysis (that we called MinVar).

Wang et al. (2015) confront the naïve one-to-one hedge ratio (that emerges as proxy for $\beta_t$ under the assumption of no basis risk, $\sigma_{sf,t} = \sigma_{f,t}^2$) and various hedge ratios within the minimum-variance framework (i.e., alternative estimates for $\beta_t$). Their analysis reveals, first, that in an out-of-sample setting, the risk coverage achieved by the naïve one-to-one hedge ratio is difficult to improve by the estimated $\beta_t$ and, second, that the rationale is both estimation error and model misspecification. We now operationalize $\beta_t$ in other ways: (a) the one-to-one hedge ratio advocated by Wang et al. (2015), and (b) through various refinements of the OLS regression model such as the bivariate VAR model, bivariate VEC model, bivariate DCC-GARCH model, bivariate BEKK-GARCH model, and Markov regime-switching OLS model.[8]

Table 7 reports the expected utility gains of the traditional hedges and corresponding selective hedges. The main evidence on the difficulty of selective hedging to consistently be more effective than traditional hedging is not challenged. For example, the expected utility gain of traditional hedging at 16.33% p.a. on average across commodities and specifications of the traditional hedge ratio is similar or slightly lower than that of the corresponding selective hedges at 16.66% (K-Integr), 15.62% (HistAve), 15.60% (EWC), 13.48% (AR), 9.62% (VAR) and 7.15% (RF) p.a.

[Insert Table 7 around here]

Table 7 also shows that the average utility gain of the MinVar hedge (16.27%) is very similar to that of the one-to-one traditional hedge (15.97%). Unreported results based on McCracken and Valente (2018) $p$-values for the null hypothesis $H_0$: $\Delta E(U_{MinVar}) \leq \Delta E(U_{One-to-One})$ versus $H_1$: $\Delta E(U_{MinVar}) > \Delta E(U_{One-to-One})$ show that for the majority of commodities the MinVar hedge does not significantly outperform the naïve one-to-one hedge. As per the recommendations of Wang et al. (2015), producers might therefore prefer the simplicity of the one-to-one hedge.

*5.2. Alternative specifications of the selective hedging strategies*

We now consider alternative designs of the selective hedging strategies. The goal is to provide more comprehensive evidence by deploying novel selective hedging approaches and, in turn, to give the selective hedging paradigm an ample opportunity to improve upon traditional hedging.

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[8] 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.

We first consider different specifications of the EWC selective hedging strategies. Some general predictors may contaminate the forecast combination with noise. To address this concern, we focus the EWC selective hedge on the 10 commodity-specific features with well-established predictive ability in the commodity literature, and on the three characteristics (roll-yield, momentum, and value) of Barroso et al. (2022). The results suggest that trimming down the information set erodes the expected utility gain of the EWC selective hedge as shown in the "*K*=10" or "*K*=3" columns of Table 8, Panel A. Thus, the difficulty of consistently outperforming traditional hedging remains.

[Insert Table 8 around here]

Motivated by the literature on stock return forecasting (Rapach et al., 2010; Neely et al., 2014; Rapach and Zhou, 2022), we also depart from the equal-weighting approach used in the EWC hedge to combine the univariate regression forecasts. In particular, we weigh the forecasts by the inverse of their past mean squared errors (MSE) or according to an Elastic Net (E-Net) algorithm (Hollstein et al., 2021; Rapach and Zhou, 2022). Details on the MSE and E-Net approaches are provided in Appendix B. Table 8, Panel A, shows that the EWC selective hedge is very competitive vis-à-vis the MSE and E-Net variants and hence, our main finding holds.

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 deploy several variants of the K-Integr selective hedge which, according to our main analysis, is the closest competitor to MinVar. We begin by deploying K-Integr on the two subsets ($K = 10$ and $K = 3$) of commodity characteristics as predictors. We then incorporate a novel

Elastic Net (E-Net) regularization into the objective function, Equation (3), as detailed in Appendix C. We also modify the tracking error constraint in Equation (3) from $\varsigma = 2\%$ p.a. to a softer $\varsigma = \{5\%, 10\%\}$ which allows the K-Integr hedge to deviate more from the MinVar hedge (benchmark) and thus, the speculative component can play a larger role. As shown in Table 8, Panel B, the expected utility gain of any of these K-Integr hedges is similar to the expected utility gain of the MinVar hedge, which confirms the difficulty of beating the much simpler to estimate MinVar hedge ratio. It is worth noting that when we deploy the K-Integr hedge portfolio in a way that permits its returns to deviate more from the MinVar hedge portfolio returns by increasing $\varsigma$ (i.e., a larger role is allowed to speculation) the expected utility gain of the K-Integr hedge decreases.

We deploy another version of the K-Integr hedge by pooling the data. The goal is to harness any increase in the estimation efficiency of the $K \times 1$ loadings $\boldsymbol{\omega_t}$ of the commodity futures predictors $\boldsymbol{z}_t$. Specifically, the representative hedger solves the same optimization problem, Equation (3), using pooled data across $N = 24$ commodities – thus, at each hedge formation time the hedger uses a sample of size of at most $T \times N$ for each variable. The outcome is a single vector of loadings $\widehat{\boldsymbol{\omega_t}}$ that exploits both the time variation and cross-sectional variation in the data (instead of the individual $\widehat{\omega}_{i,t}, i = 1, \dots, N$ obtained from the time-series estimation of the K-Integr hedge in Section 4). The results in the last column of Table 8, Panel B, suggest that the expected utility gain of the pooled K-Integr hedge at 16.63% p.a. across commodities is nearly identical to the 16.61% p.a. expected utility gain obtained on average in Table 3 for the K-Integr hedges deployed per commodity.[9] Altogether the results from various K-Integr hedges reiterate that commodity producers should not embed a speculative motive into their hedging programs.

Next, we deploy additional selective hedges that harness forecasts from state-of-the-art machine learning methods over and above the random forests (RF) deployed earlier. For consistency, we begin by deploying the RF with the smaller subsets of predictors ($K$=10 or $K$=3 commodity characteristics). 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 in each respective layer) and three hidden layers (DNN3 with 32, 16 and 8 nodes). These same DNN architectures are then augmented with 4 or 8 long-short term memory (LSTM) hidden units which are intended to capture long-run nonlinear predictability patterns.[10] Table 8, Panel C, presents the results. None of these sophisticated selective hedges affords higher expected utility gains than the MinVar hedge, which is not surprising since the (unreported) $R^2_{OOS}$ measures of the machine-learning forecasts are generally negative or zero suggesting that they do not outperform the zero-return forecast benchmark. This finding is aligned with the mixed results in Wang and Zhang (2024) on the ability of machine learning methods to predict individual

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[9] This inference is unchanged if we add the E-Net regularization to the panel or if we adopt the softer tracking error constraints $\varsigma = \{\ 5\%, 10\%\}$.

[10] The steps of these machine learning approaches are similar to those of the RF approach, as detailed in Section 4.1, but the estimation is based on a maximum number of epochs (set at 100), batch size (20% of trained sample), patience (5), learning rate (0.001 or 0.01), Adam optimization with Huber loss function (transition coefficient at 99.9% quantile); and the overfitting penalties are early stopping, dropout layer (5%), batch normalization, ensemble net (500) and *l2* regularization ($10^{-5}$ or $10^{-3}$). The number of LSTM units follows from Chen et al. (2023) and Rad et al. (2023).

commodity futures returns, and more generally with the comprehensive evidence in Cakici et al. (2023) who challenge the practical utility of machine learning methods to predict stock returns.[11]

Since the seminal paper of Bates and Granger (1969), the combination of forecasts from different methods has been advocated in the literature to reduce the out-of-sample mean squared error. Thus, we deploy a selective hedge (denoted Comb) that uses as input the equal-weighted combination of the competing forecasts: HistAve, AR, VAR, EWC, K-Integr, and RF. We observe an improvement from the Comb selective hedge, but the MinVar hedge remains difficult to beat.

Next, we implement a selective hedge that uses as inputs the futures returns forecasts from cross-sectional (CS) predictive regressions in the spirit of Fama and MacBeth (1973) and Lewellen (2015). First, we estimate each week the slopes from cross-sectional regressions of the commodity futures returns at week $t$ on commodity-specific characteristics at week $t$-1. The estimated cross-sectional slopes are then averaged over the 10 years preceding hedging decision and these averages are used, alongside the most recent commodity characteristics, to forecast commodity futures returns one week ahead. Table 8, Panel D, shows that the CS selective hedge (using $K$=10 and $K$=3 predictors) does not outperform the MinVar hedge regardless of the information set considered.

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. Specifically, we construct a Naïve Basis

[11] We expand the information set of the ML models using the FRED-MD database of McCraken and Ng (2016) from Dr. M. McCraken's website. We augment the 126 FRED-MD series with the 15 financial, macroeconomic and sentiment predictors from Appendix A that are excluded from McCracken and Ng (2016), extract 8 principal components from the augmented dataset and complement it with the 10 commodity-specific predictors. This alternative information set does not challenge our main finding on the difficulty of outperforming MinVar.

selective hedge using the forecast $E_t(\Delta f_{t+1}|\Omega_t) = \frac{ryield_t}{D_t} \times 7$ where $ryield_t = f_{t,1} - f_{t,2}$, with $f_{t,1}$ and $f_{t,2}$ the log prices of the front and second-nearest contracts, respectively, and $D_t$ the number of calendar days between their maturities. As seen 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 time specific, we deploy the strategies over subsamples. We classify the sample weeks as *i*) pre versus post financialization (dated January 2006, Stoll and Whaley, 2010), *ii*) backwardated versus contangoed (positive versus negative commodity-specific roll-yields), *iii*) U.S. recessions versus expansions (NBER) and *iv*) high versus low volatility. The volatility split is defined relative to the median value of two volatility measures: the GARCH(1,1) volatilities of each commodity spot returns and the macro uncertainty index of Jurado et al. (2015). The expected utility gains of the hedging strategies over subsamples, shown in Table 9, support our finding that it is very difficult for selective hedging to consistently outperform traditional hedging. The results also confirm the economic intuition that commodity producers extract more utility from hedging in contango, during recessions, and in periods of high volatility.

[Insert Table 9 around here]

*5.4. Non-constant risk aversion*

Thus far we have assumed a constant coefficient of relative risk aversion ($\gamma = 5$). Now we deploy the selective hedge ratio $h_t = \beta_t - \frac{E_t(\Delta f_{t+1}|\Omega_t)}{\gamma_t \, \sigma_{f,t}^2}$ adopting as values for $\gamma_t$ the relative risk aversion estimated by Bekaert et al. (2022) which has an average value of 3.0624 over our sample period. Thus, the speculative term plays a larger (smaller) role in periods of low (high) risk aversion. Table 10 reports the expected utility gains obtained for the various hedges and corroborates the difficulty of outperforming the traditional MinVar hedge. The expected utility gain of MinVar (9.41% p.a.) is similar to that of the K-Integr hedge (9.83% p.a.) and superior to those of the HistAve, EWC, RF and AR hedges (at 8.58%, 8.54%, 6.01% and 4.70% p.a., respectively). The expected utility gain of the VAR hedge is negative (-1.71% p.a.), suggesting that producers are better off by not hedging their commodity spot risk at all rather than by selectively hedging it upon VAR forecasts.

[Insert Table 10 around here]

*5.5. Estimation window and rebalancing frequency*

Our investigation thus far has relied on hedge ratios constructed with past rolling estimation windows of length $L$ =520 weeks (10 years) which are rebalanced weekly. The expected utility gains obtained with expanding windows (starting with $L$ = 520 weeks, and adding one week at a time), as shown in Table 10, are very similar to those from the rolling window analysis in Table 3.

Given that the commodity hedging literature has predominantly adopted 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, the weekly hedging frequency we use can be seen as a reasonable middle-ground.[12] Nevertheless, in this robustness test we consider monthly (month-end settlement prices) and quarterly (quarter-end settlement prices) rebalancing. The lower rebalancing improves hedging utility for both traditional and selective hedging, as seen in Table 10, but the main finding that traditional hedging is difficult to outperform remains.

*5.6. Alternative futures maturities*

[12] 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.

We have implemented the hedges with front-end futures contracts. As a robustness, we construct hedges that use instead the second (third, fourth, fifth or sixth) maturity contracts along the futures curve, where each contract is held up to the last day of the month preceding the maturity of the front-end contract with the position then rolled to the then third (fourth, fifth, sixth or seventh, respectively) contract. The results, presented in Table 10, highlight the superiority across maturities of the MinVar and K-Integr hedges in terms of expected utility gains. The expected utility gains decrease with the maturities of the hedging instruments due to an increase in basis risk.

*5.7. Long hedging*

The representative hedger is thus far a commodity producer, that is, the traditional hedge is short. We now address the hedging problem of a processor or a consumer of the physical commodity (long hedger) with hedge portfolio return 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 is the traditional MinVar hedge ratio, $\beta_t = \frac{\sigma_{sf,t}}{\sigma_{f,t}^2}$, and the second component is speculative.

The last row of Table 10 presents the expected utility gains of the long hedges. Over the sample period under study, the expected utility gain of short hedging is 4.87% p.a. higher than that obtained via long hedging on average across commodities and hedging strategies (c.f., Table 3). However, this average across commodities conceals large heterogeneity. For example, unreported results show that for natural gas the expected utility gain of short hedging exceeds that of long hedging by 53.47% p.a. on average across hedging strategies, while for unleaded gasoline the expected utility gain of long hedging is 26.69% p.a. larger than that of short hedging. This notwithstanding, our main conclusion remains: 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 markets hedging literature in formalizing and examining empirically the hedging problem at the individual commodity level (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 K-Integr hedging setting of Barroso et al. (2022), we now consider a firm that produces various commodities. Without loss of generality, we assume that the diversified commodity producer has equal exposure $1/N$ to the commodities (i.e., $N = 24$). 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 $\sigma\left(\widetilde{\Delta p}_{t+1}^{MinVar} - \widetilde{\Delta p}_{t+1}^{K-Integr}(\boldsymbol{\omega_t})\right) \leq \varsigma$ in order to identify the loadings $\boldsymbol{\omega_t}$ that maximize the expected utility of the cross-commodity hedge portfolio return,

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

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

where the $i$th commodity spot return and futures return are given by $\Delta s_{i,t+1}$ and $\Delta f_{i,t+1}$, and its MinVar hedge ratio by $\beta_{i,t}$. The return of the cross-commodity MinVar portfolio $\widetilde{\Delta p}_{t+1}^{MinVar} = \frac{1}{N}\sum_{i=1}^{N}\left(\Delta s_{i,t+1} - \beta_{i,t}\Delta f_{i,t+1}\right)$ arises from Equation (7) by setting $\boldsymbol{\omega_t} = 0$ to mute the speculative component**.** It is worth noting that this K-Integr hedge constraints the unknown coefficients $\boldsymbol{\omega_t} = (\omega_{1,t}, \ldots, \omega_{K,t})'$ to be common across commodities so that it is similar to the parametric portfolio policies (PPP) approach where the vector of loadings on asset characteristics is the same for all assets over time (e.g., Brandt et al., 2009; Barroso et al., 2022).[13] The results suggest that with an expected utility gain of 4.00% p.a., the cross-commodity K-Integr hedge improves upon the cross-commodity traditional MinVar hedge (3.48% p.a.) but the differential is not statistically significant as suggested by the *p*-value of the McCraken-Valente test for difference in expected utility gains (0.26). Therefore, selective hedging is not significantly more effective than traditional hedging for a diversified commodity producer either.

## 6. Conclusions

This article provides a comprehensive analysis of traditional and selective hedging strategies in commodity futures markets. Traditional minimum-variance hedging is found to provide expected utility gains that are at least as high as those obtained with selective hedging. The difficulty of selective hedging to outperform traditional hedging reflects the low out-of-sample time-series predictability of individual commodity futures returns – the forecasts obtained increase the risk of the hedge portfolio without generating an additional return. These findings hold for a large spectrum of commodities, different methods to construct commodity futures return forecasts, alternative specifications of the traditional hedge ratios, and various subsamples, estimation windows, and hedge rebalancing frequencies inter alia.

Selective hedging strategies based on publicly available information fail to deliver strong and consistent outperformance relative to traditional hedging. Our strong recommendation therefore is

[13] Leaving aside the spot return, the return of the cross-commodity K-Integr hedge is similar to the return of the PPP portfolio in that both comprise a benchmark portfolio return and a characteristics portfolio return. However, while K-Integr uses both commodity characteristics and financial, macroeconomic and sentiment variables as predictors, in the PPP setting of Brandt et al. (2009) and Barroso et al. (2022) deviations from the benchmark return depend solely on asset characteristics.

that commodity traders shall not abandon traditional hedging in favor of selective hedging. This message echoes the concerns raised from the analysis of specific speculative-led commodity hedging fiascos (Pirrong, 1997; Carter et al., 2021; Westgaard et al., 2022) and is aligned with the evidence on the (at-best) small increases in firm value obtained through selective hedging (Adam and Fernando, 2006; Brown et al., 2006). The conclusion drawn is based on futures return predictions that exploit publicly available information, which leaves open the possibility that private information might help in designing better selective hedges. While we acknowledge this limitation, we endorse traditional hedging over selective hedging to those firms that do not have consistent and substantial access to reliable private information.

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## Appendix A: Commodity futures return predictors.

| 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 | $f_{t,1} - f_{t,2}$ | Refinitiv Datastream | Szymanowska et al. (2014) |
| Momentum | Front-end log excess returns averaged over the previous year | $\frac{1}{52}\sum_{j=0}^{51} \Delta f_{t-j,1}$ | Refinitiv 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 $t$ | $\left(\frac{1}{D}\sum_{d=0}^{D-1} f_{t-d,1}\right) - f_{t,1}$ | Refinitiv 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 on the prior year | $\frac{1}{52}\sum_{j=0}^{51} \Delta f_{t-j,1} - \frac{1}{52}\sum_{j=0}^{51} \Delta f_{t-j,2}$ | Refinitiv Datastream | |
| Skewness | Third moment of the $D$ daily front-end excess returns within the past year | $\frac{1}{D}\frac{\sum_{d=0}^{D-1}\left(\Delta f_{t-d,1} - \mu_t\right)^3}{\sigma_t^3}$ | Refinitiv Datastream | Fernandez-Perez et al. (2018) |
| Relative basis | Difference in front- and second-nearest roll-yields | $\left(f_{t,1} - f_{t,2}\right) - \left(f_{t,2} - f_{t,3}\right)$ | Refinitiv 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 | $\frac{1}{W}\sum_{j=0}^{W-1} \frac{\lvert\Delta f_{t-j,1}\rvert}{\$Volume_{t-j}}$ | Refinitiv Datastream | Szymanowska et al. (2014) |
| Change in open interest | Change in the average open interest along the futures curve | $OI_t - OI_{t-1}$ | Refinitiv Datastream | Hong and Yogo (2012) |
| **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 returns | 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 | | Refinitiv 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 | | Refinitiv 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 | | Refinitiv Datastream | Hollstein et al. (2021) |

LH (SH) denotes the long (short) positions of large hedgers. A positive (negative) hedging pressure indicates net short (long) hedging and thus backwardation (contango). (*) indicates that we employ weekly interpolation, that is, the weekly values are set at the highest frequency available value which are monthly. (**) indicates that we use the two-month lagged time-series to accommodate delays in data publication release.

## Appendix B: Alternative specifications of the EWC selective hedge

The EWC hedge ratio is based on expectations of futures returns derived from the combination of univariate forecasts from $K$ predictors; $E_t(\Delta f_{t+1}|\Omega_t) = \boldsymbol{\omega}_t'\Delta\hat{\boldsymbol{f}}_{t+1}$ with $\Delta\hat{f}_{k,t+1} = \hat{\alpha}_{0,t} + \hat{\alpha}_{1,t}z_{k,t}$, $k = 1, \dots, K$, 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 depends on forecast accuracy, with higher weights assigned to the forecasts with lower mean squared error (MSE). The weights are calculated as follows. Each hedge formation week *t*, the window of $L = 520$ weeks is divided into an estimation window and an evaluation or holdout window of equal length ($L_0 = L_1 = \frac{L}{2}$). The first $L_0$ weeks are used to generate the $K$ out-of-sample univariate forecasts of futures returns, $\Delta\hat{f}_{k,t+1}$, for the first week of the evaluation period. The estimation window is then expanded by one week and a second set of $K$ forecasts is generated for the second week of the evaluation period, and so forth. The MSE is calculated over the $L_1$ period as $MSE_{k,t} = \sum_{j=0}^{L_1-1}(\Delta f_{t-j+1} - \Delta\hat{f}_{k,t-j+1})^2/L_1$ . The weighting scheme used at time $t$ to generate $E_t(\Delta f_{t+1}|\Omega_t)$ is then $\omega_{k,t} = \frac{MSE_{k,t}^{-1}}{\sum_{k=1}^{K} MSE_{k,t}^{-1}}$. This procedure is repeated at the next rebalancing time $t$+1.

### 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 prior $L = 520$ weeks window into an estimation window and an evaluation (holdout) window ($L_0 = L_1 = \frac{L}{2}$) and repeat the steps for MSE weighting scheme to obtain the forecasts over the evaluation window, $L_1$. Then, we solve the following minimization problem over the evaluation period,

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

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

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

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

subject to the constraint $\sigma\left(\Delta p_{t+1}^{MinVar} - \Delta p_{t+1}^{K-Integr}(\boldsymbol{\omega_t})\right) \leq \varsigma$. $\Delta s_{t+1}$, $\Delta f_{t+1}$, $\Delta p_{t+1}^{K-Integr}$ and $\Delta p_{t+1}^{MinVar}$ are the spot, futures, K-Integr and MinVar returns for a given commodity *i* at time *t*+1, respectively, $\beta_t$ 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 $\lambda_t$, 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 $\lambda_t$ (i.e., twenty evenly-spaced values from 0.0073 to 0.00001). Third, we select the $\lambda_t$ value that generates the largest expected utility of the optimized portfolio over the evaluation sample. Finally, the selected $\lambda_t$ 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 (in black) and six alternative selective hedge ratios (in grey) for a representative cocoa producer with assumed mean-variance utility function and coefficient of relative risk aversion $\gamma = 5$. The rebalancing frequency is weekly.

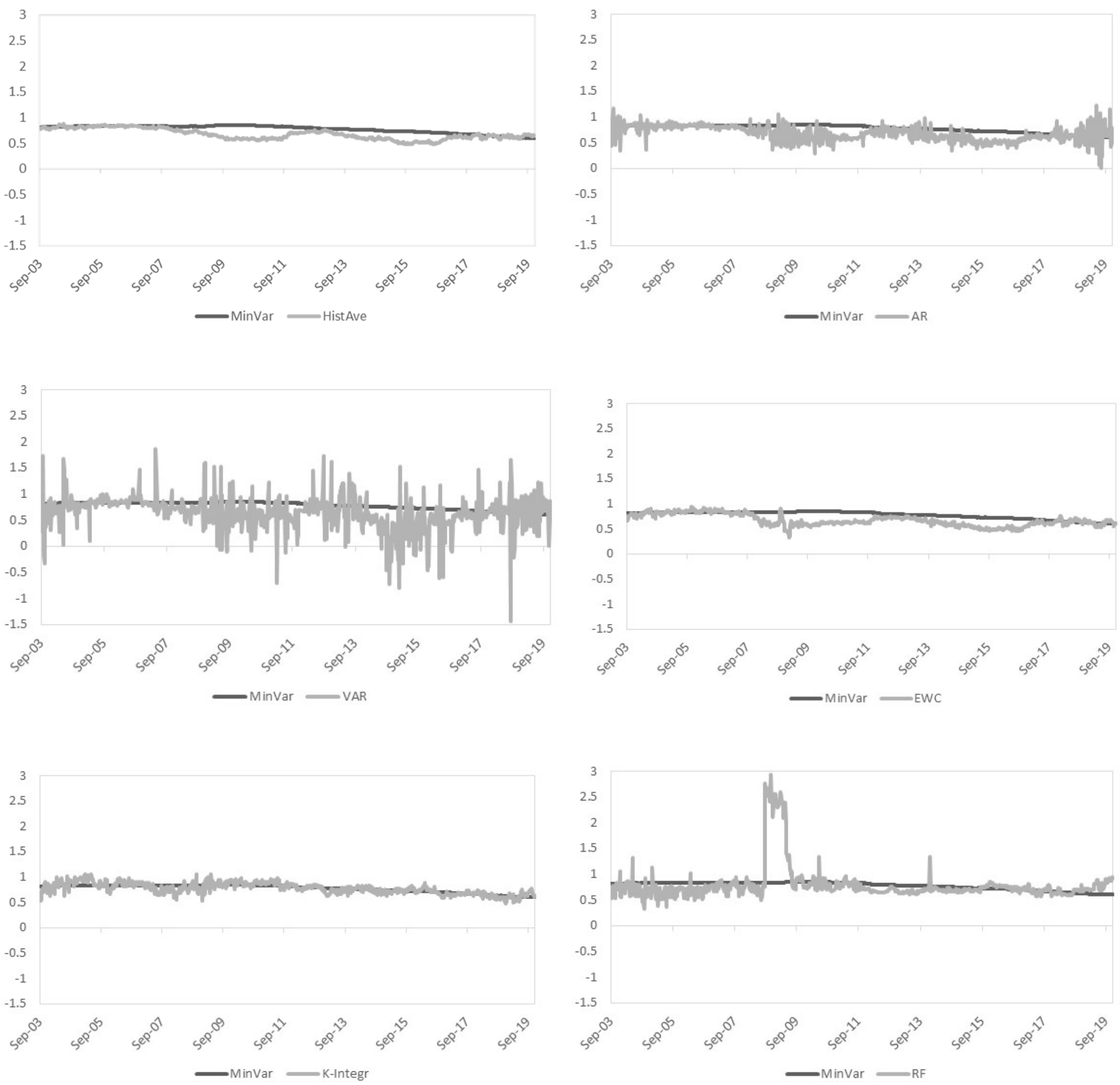

**Figure 2. Standard deviation of the hedge ratios**

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

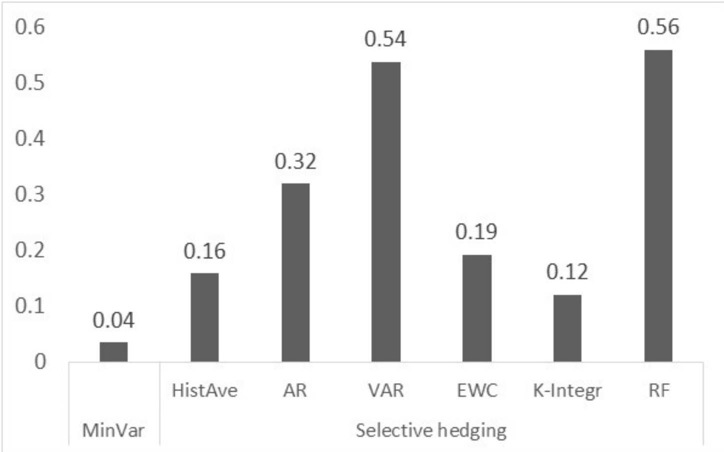

**Table 1. Selective hedging strategies.**

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

*Note*: $\beta_t$ is the traditional MinVar hedge ratio that minimizes the variance of the hedge portfolio.

**Table 2. Descriptive statistics of spot and futures returns.**

The table presents summary statistics for the 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 for the significance of the mean return are in parentheses and $p$-values for the significance of the correlation are in curly brackets. The last two columns report the data span.

| | 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.**

The table reports the annualized expected utility gains achieved by the traditional MinVar and selective hedging strategies derived with HistAve, AR, VAR, EWC, K-Integr and RF forecasts. The utility function is mean-variance with 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 (c.f. Table 2). The numbers in parentheses are bootstrap $p$-values for the McCracken and Valente (2018) statistic with $H_0: \Delta E(U_{Diff}) = \Delta E(U_{SH}) - \Delta E(U_{MinVar}) \leq 0$ versus $H_1: \Delta E(U_{Diff}) > 0$, where $\Delta E(U)$ is the expected utility gain as defined in Equation (4) and $SH$ stands for the selective hedging strategy at hand. The average expected utility gains across commodities are summarized in Panel E before and after transaction costs (TC) of 8.6 basis points (Marshall et al., 2012). The sample periods are as 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.**

The table reports the OOS-$R^2$ statistic that gives the reduction in out-of-sample mean squared error of the futures return forecast used in each selective hedge versus the zero-return (no predictability) benchmark that underlies the MinVar hedge. A negative or zero OOS-$R^2$ suggest that the futures return forecast at hand is less or as accurate as the zero-return forecast. $p$-values of the Diebold and Mariano (1995) test are shown in parentheses. The sample periods are as detailed in Table 2.

| | HistAve | | AR | | VAR | | EWC | | K-Integr | | RF | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Panel A: Agriculture** | | | | | | | | | | | | |
| Cocoa | -0.32% | (0.955) | -0.52% | (0.982) | -1.32% | (0.996) | -0.46% | (0.981) | 0.05% | (0.368) | -0.87% | (0.793) |
| Coffee | -0.34% | (0.971) | -1.14% | (0.989) | -1.66% | (0.974) | -0.25% | (0.906) | 0.16% | (0.113) | -0.69% | (0.840) |
| Corn | -0.31% | (0.897) | -0.72% | (0.889) | -0.93% | (0.893) | -0.38% | (0.909) | -0.01% | (0.538) | 0.72% | (0.247) |
| Cotton | -0.45% | (0.934) | -0.85% | (0.985) | -2.07% | (1.000) | -0.46% | (0.889) | 0.03% | (0.423) | -0.53% | (0.687) |
| Frozen orange juice | -0.32% | (0.992) | -0.66% | (0.909) | -1.76% | (0.977) | -0.35% | (0.970) | -0.09% | (0.808) | -0.23% | (0.654) |
| Soybeans | -0.06% | (0.569) | -0.35% | (0.736) | -0.97% | (0.886) | -0.13% | (0.626) | 0.13% | (0.152) | -0.35% | (0.590) |
| Soybeans meal | 0.06% | (0.460) | -0.73% | (0.810) | -2.13% | (0.979) | 0.08% | (0.449) | 0.17% | (0.118) | -0.89% | (0.756) |
| Soybeans oil | -0.24% | (0.913) | -0.48% | (0.944) | -0.36% | (0.747) | -0.32% | (0.923) | 0.08% | (0.257) | 0.11% | (0.469) |
| Sugar | -0.23% | (0.850) | -0.54% | (0.910) | -0.81% | (0.949) | -0.24% | (0.850) | 0.20% | (0.100) | -0.70% | (0.835) |
| Wheat | -0.20% | (0.761) | -0.66% | (0.917) | -1.22% | (0.968) | -0.17% | (0.716) | -0.04% | (0.627) | -0.50% | (0.722) |
| **Panel B: Energy** | | | | | | | | | | | | |
| Crude oil | -0.30% | (0.721) | -0.76% | (0.848) | -2.52% | (0.990) | 0.08% | (0.431) | 0.07% | (0.306) | 0.70% | (0.276) |
| Gasoline RBOB | -0.53% | (0.711) | 2.61% | (0.053) | -1.22% | (0.620) | -0.88% | (0.786) | -1.04% | (0.704) | 0.09% | (0.458) |
| Heating oil | -0.29% | (0.712) | -0.56% | (0.766) | -1.26% | (0.925) | 0.04% | (0.463) | 0.12% | (0.197) | 0.71% | (0.278) |
| Natural gas | 0.45% | (0.204) | 0.08% | (0.451) | -1.95% | (0.950) | 0.63% | (0.137) | 0.09% | (0.257) | 0.62% | (0.105) |
| Unleaded gas | 0.88% | (0.274) | 0.50% | (0.393) | -0.93% | (0.669) | 0.92% | (0.273) | 0.02% | (0.471) | 0.70% | (0.064) |
| **Panel C: Livestock** | | | | | | | | | | | | |
| Feeder cattle | -0.19% | (0.643) | -0.49% | (0.663) | -1.02% | (0.798) | -0.15% | (0.612) | 0.11% | (0.260) | -2.37% | (0.879) |
| Lean hogs | 0.00% | (0.501) | 0.21% | (0.325) | -0.47% | (0.785) | 0.05% | (0.454) | 0.24% | (0.176) | 0.50% | (0.306) |
| Live cattle | -0.36% | (0.886) | -0.98% | (0.895) | -0.76% | (0.840) | -0.35% | (0.860) | 0.24% | (0.031) | -0.76% | (0.756) |
| **Panel D: Metal** | | | | | | | | | | | | |
| Copper | -0.32% | (0.724) | -0.68% | (0.875) | -0.69% | (0.821) | -0.10% | (0.569) | 0.08% | (0.261) | -0.20% | (0.539) |
| Gold | -0.12% | (0.586) | -0.39% | (0.739) | -1.42% | (0.981) | -0.28% | (0.691) | -0.21% | (0.951) | -3.53% | (0.959) |
| Lumber | -0.16% | (0.635) | -0.37% | (0.776) | -0.09% | (0.567) | -0.17% | (0.642) | 0.16% | (0.112) | 0.31% | (0.312) |
| Palladium | 0.00% | (0.506) | 0.08% | (0.399) | -1.58% | (0.987) | 0.06% | (0.431) | 0.20% | (0.192) | -1.03% | (0.911) |
| Platinum | -0.23% | (0.631) | -0.79% | (0.796) | -1.81% | (0.964) | -0.16% | (0.602) | -0.13% | (0.719) | -1.04% | (0.732) |
| Silver | -0.27% | (0.774) | -0.82% | (0.955) | -1.30% | (0.971) | -0.36% | (0.830) | -0.06% | (0.676) | -1.09% | (0.890) |

**Table 5. Abnormal return of the selective hedges.**

The 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. Significance Newey-West *t*-statistics are shown in parentheses (using Andrews and Monohan, 1992, to determine the lag selection parameter). The sample periods are as detailed in Table 2.

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

**Table 6. Risk reduction ability of the hedges.**

The 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 periods are as 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** | **Selective hedges** | | | | | |
|---|---|---|---|---|---|---|---|
| | **hedge** | **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.**

The table reports the annualized expected utility gains obtained from alternative specifications of the EWC (Panel A), K-Integr (Panel B), RF (Panel C) and miscellaneous (Panel D) selective hedging strategies. The first column of Panels A to C pertain to the baseline setting of Table 3. '$K$=10', and '$K$=3' refer to the 10 commodity-specific predictors and to 3 commodity predictors (roll-yield, momentum and value), respectively. In Panel A, MSE and E-Net combine the predictions from univariate regressions using either the inverse of the mean squared errors or elastic net weights as detailed in Appendix B. PC1 (PC1-2) use the first (two first) principal component(s) of the full set of information variables as predictors. In Panel B, K-Integr E-net includes an elastic-net penalty for overfitting as detailed in Appendix C, $\varsigma$ is the tracking error threshold, Pooled K-Integr stacks together all the commodities and predictors before optimizing the weights. In Panel C, DNN stands for deep neural network with the number of hidden layers mentioned thereafter, LSTM stands for long-short term memory network with the number of LSTM units mentioned thereafter. In Panel D, Comb combines the predictions of all the six selective hedging models of Table 3, CS relies on Fama-MacBeth cross sectional forecasts. Naïve Basis uses the roll-yield at time $t$ as futures return forecast. The expected utility gains are averaged 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) | Naive Basis | | | | | |
| 0.1630 | 0.1335 | 0.1456 | 0.0465 | | | | | |

**Table 9. Subsample analysis.**

The table reports the annualized expected utility gains of the various hedging strategies over different subsample periods such as pre and post the financialization of commodities using the January 2006 date suggested by Stoll and Whaley (2010), during backwardation and contango periods, during NBER expansions and recessions, during periods of high versus low commodity market volatility (defined according to a GARCH model fitted to weekly spot returns), and high versus low macro volatility (relative to the macroeconomic uncertainty index of Jurado et al., 2015). The expected utility gains reported are averages across commodities. They are calculated using returns that are contemporaneous to the subsamples. The sample splits are determined ex-post based on the full sample series.

| | 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.**

The table presents the annualized expected utility gains of various hedging strategies obtained when allowing for time-variation in the hedger's risk aversion, from 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 recalls the baseline results of Table 3. Unless otherwise stated, the utility function is mean-variance with coefficient of relative risk aversion $\gamma = 5$. The expected utility gains reported 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 |