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MASTER THESIS

Hedge Ratio Estimation in Inventory Management

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Declaration of Authorship

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Signature

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Abstract

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Companies dependent on commodities for their production have to deal with volatile commodity prices and should employ measures for risk reduction as unfavourable spot price development may cause significant losses. A useful tool for diminishing the risk is hedging on futures market; however, this approach faces a crucial question of optimal hedge ratio determination (ratio between spot and futures units). Our thesis examines nine different ways of optimal hedge ratio estimation (naive, Sharpe, mean extended Gini coefficient, generalized semivariance, value at risk, and minimum variance through OLS, error correction, GARCH, and bivariate GARCH models) and evaluates their efficiency using the data on eight different commodities. The results differ across the respective commodities and cannot be generalized. Two conclusions resulting from the analysis refer to performance of naive and OLS hedge ratios and constant vs time varying hedge ratios. We find that complex hedge ratios, such as bivariate GARCH or VaR hedge ratios, do not outperform naive and OLS hedge ratios and that the results of constant hedge ratios are mostly as good as results of time-varying hedge ratios.

Keywords optimal hedge ratio, commodities, efficiency

Abstrakt

Název:	Odhad zajišťovacího poměru v řízení zásob
Autor:	Barbora Máková
Katedra:	Katedra ekonometrie
Vedoucí práce:	doc. RNDr. Ing. Michal Černý, Ph.D.

Společnosti, jejichž výroba je závislá na komoditách, jsou vystaveny volatilitě cen komodit, která může způsobit významné ztráty. Proto by tyto společnosti měli využít opatření vedoucí ke snížení rizika plynoucího z volatility. Užitečným nástrojem pro kontrolu risku je zajištění spotové pozice na trhu s futures, tento přístup se však setkává s problémem, jak určit optimální zajišťovácí poměr (poměr mezi počtem jednotek ve spotové a futures pozici). Tato teze zkoumá devět různých metod odhadování optimálního zajišťovacího poměru (naivní, Sharpe, průměrný rozšířený Gini koeficient, rozšířená semivariance, value at risk a minimální rozptyl pomocí metody nejmenších čtverců, korekce chyb, GARCH a dvourozměrného GARCH modelu) a hodnotí jejich účinnost pro osm různých komodit. Výsledky se pro různé komodity liší, a proto nemohou být zobecněny. Na základě naší analýzy můžeme udělat dva závěry týkající se účinnosti naivního zajišťovacího poměru a zajišťovacího poměru získaného pomocí metody nejmenjších čtverců a konstantního vs. časově proměnného zajišťovacího poměru. Zjistili jsme, že složité zajišťovací poměry založené na dvourozměrném GARCH modelu nebo value at risk nejsou účinnější než jednoduché zajišťovací poměry (naivní, založené na metodě nejmenších čtverců) a že účinnost konstantního zajišťovacího poměru je pro většinu komodit stejně dobrá jako účinnost časově proměnných zajišťovacích poměrů.

Klíčová slova optimální zajišťovací poměr, komodity, účinnost

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Acronyms

bGARCH Bivariate Generalized Autoregressive Conditional Heteroskedasticity

CBOT Chicago Board of Trade

CME Chicago Mercantile Exchange

COMEX Commodity Exchange, Inc.

ECM Error Correction Model

GARCH Generalized Autoregressive Conditional Heteroskedasticity

GSV Generalized Semivariance

HR Hedge Ratio

ICE IntercontinentalExchange

MEG Mean Extended-Gini Coefficient

NYMEX New York Mercantile Exchange

OLS Ordinary Least Squares

VaR Value at Risk

WSJ MDC Wall Street Journal Market Data Center

Chapter 1

Introduction

Risk is an integral part of most human activities. Modern society is aware of ubiquity of risk and tries to measure its magnitude, evaluates its impact, and develops tools for mitigation of its negative effects. Our thesis deals with the problem of commodity price volatility and examines several ways how to reduce its undesirable effects. Managing this type of risk is extremely important as it affects nearly every company. Further, commodity price volatility has been increasing over time, which can be tracked using volatility of one of the most important global commodity price indices - Standard & Poor Goldman Sachs Commodity Index; the yearly volatility was 13 percent in 1981, then increased to 20 percent and regularly exceeded this level in 2000's; finally, it reached 23 percent in 2011.

Companies dependent on commodities for their production have had to deal with volatile commodity prices for years. Unpredictable spot price development has negative influence on creation of a company's business plan and may cause significant losses. Nonetheless, many companies do not manage price volatility and some of them are not even aware of their exposures. Hedging of a spot position on futures market is a simple way how to avoid the losses. It secures the spot position by taking an opposite position in futures, whose returns are correlated with the spot returns; hence, a loss in terms of spot value is balanced by a gain in futures value, the risk in terms of variance decreases, and the income is stabilized. The crucial problem is setting the optimal ratio between units of futures and spot assets; this ratio is called hedge ratio.

There are many strategies that can be employed for hedging and they differ in the complexity of optimal hedge ratio estimation. A hedger may choose from a variety of hedging ratios stretching from simple hedge ratios, i.e. naive hedge ratio, OLS hedge ratio, to complex hedge ratios, i.e. bivariate GARCH hedge ratio or VaR hedge ratio. Moreover, hedging does not have to focus on variance minimization, mean returns may be taken into account as well. We provide a comprehensive analysis of both minimum variance and mean variance hedge ratios and examine their efficiency for eight different commodities. The following types of hedge ratios are studied: naive, minimum variance, Sharpe, mean extended Gini coefficient, generalized semivariance, and Value at Risk hedge ratios. The minimum variance hedge ratios are estimated based on OLS, error correction model, GARCH and bivariate GARCH models. We examine a wide range of commodities that includes: Beef, Coffee, Copper, Corn, Oil, Platinum, Soybeans, and Wheat. We use daily data from May 1, 2007 to August 31, 2013 period, divide the dataset to in-sample and out-of-sample parts and compare efficiency of daily changing hedge ratios, weekly changing hedge ratios and constant hedge ratios. The efficiency is measured by reduction in variance and Value at Risk. As far as we know, this is the first study comparing efficiency of all the above mentioned hedge ratios for a wide range of commodities; the thesis thus makes a considerable empirical contribution to the existing literature as it allows a direct comparison of various approaches. Moreover, it can be used by companies as a guide for choosing the optimal hedge ratio.

We find that the efficiency of individual hedge ratios significantly differs for the examined commodities and it is impossible to make general conclusions about the quality of individual hedge ratios. Each spot position requires different type of hedging and the hedger should employ efficiency analysis of the hedging strategies before choosing the optimal hedge ratio. However, two conclusions resulting from our study can be made still: constant hedge ratios have mostly as good results as time-varying hedge ratios, and complex hedge ratios (bivariate GARCH, VaR) do not significantly outperform simple hedging strategies, such as naive hedging or OLS hedge ratio. Further, the simple hedge ratios are less costly to apply and some companies may thus favour them.

The thesis is structured as follows: the next chapter contains an introduction to futures. Chapter 3 presents an overview of the existing types of hedge ratios and the related literature, while Chapter 4 deals with methodology and detailed description of hedge ratios estimations and calculations. Consequently, Chapter 5 constitutes the principal part of the work as it examines the used data and discusses the findings of our analysis. Finally, Chapter 6 concludes the thesis.

Chapter 2

Futures

The modern history of futures began by establishment of the oldest organized futures exchange, Dojima Rice Exchange in Osaka, Japan, in 18th century (Bakken 1966). However, evidence suggest that products similar to futures contract were used thousand years ago, for example in India 2000 B.C., where merchants made consignment transactions for goods sold in India (Duffie 1989). This implies that risk management is not an achievement of modern society, people tried to evaluate costs of uncontrollable events and prevent them as early as four thousand years ago.

Futures are highly standardized contracts binding two parties – seller and buyer - to sell or buy a specific asset at a given price and time. Futures can be held to maturity or closed by buying the opposite type of contract (if you are seller in a contract you have to enter the same contract as a buyer and thus close your position; it is not a problem to close the position as the contracts are highly standardized, and only a minority of traders holds futures till maturity). It is said that sellers are in short position and buyers in long position.

Futures are traded at organized exchanges which stand as an intermediary between the two parties and diminish the risk of counter-party failure. In fact, the exchange is the official counter-party of both, buyer and seller, it enters into contract with many buyers and sellers and at the settlement day, or in case of closing the contract, it simply matches the most suitable buyer and seller. Changes in price of underlying assets are reflected daily in the futures prices and settlements occur on daily basis. For this reason, all clients must have a margin account at the exchange with a given amount of money that is used for daily settlements. At the beginning of a contract, an initial margin, higher than maintenance margin that is required to be on the account, is paid. If the money on margin account decreases under the maintenance margin level, client receives a margin call to replenish it. If she is unable to top-up the margin, her position is automatically closed. On the other hand, if the investment is successful, investor may withdraw any amount above the initial margin. This process is called marking to market and causes that the money amount exchanged on the delivery date is given by spot price not by the price specified in the contract because settling the difference on margin accounts actually resets the last day futures price F_0 to today's settlement price F_1.

We may illustrate the process on an example. We enter a futures contract on 100,000 bushels of Soybeans as a seller at $1,280 per future. As the Soybeans contract size is 5,000 bushels, we have a short position in 20 futures contract on soya beans in total value of $25,600. The initial margin is set to $100 per contract and maintenance margin is $75 per contract. As we have 20 contracts, the initial margin is $2,000 and maintenance margin takes value of $1,500. Table 2.1 shows possible futures prices at a given day, daily and cumulative gains and losses, and the development in the marginal account balance.

Table 2.1: Marginal account

Day	Futures price	D. gain/loss per contract	D. gain/loss	Cum. gain/loss	Margin account	Margin call
0	1280				2000	
1	1269	11	220	220	2220	
2	1264	5	100	320	2320	
3	1273	-9	-180	140	2140	
4	1296	-23	-460	-320	1680	
5	1307	-11	-220	-540	1460	40
6	1315	-8	-160	-700	Pos. closed	

When today's closing settlement price is lower than the previous day actual price, we make a gain as we have a future to sell the underlying asset for a higher price than for what it is settled today. The change is reflected daily on the margin account.

2.1 Hedging with futures

So if a company is engaged in producing or processing of some commodity which match the standards of futures and if a future with the desired settlement day exists, hedging is very easy – the company only enters the respective position in

Figure 2.1: Spot and futures prices converging

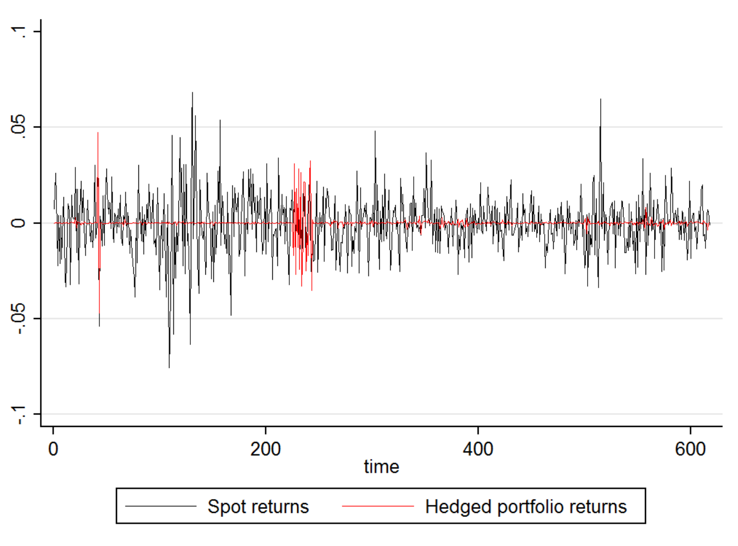
required number of contracts and waits until the settlement day. For example, a farmer producing corn of a quality standardized by an exchange knows that she will produce approximately 200,000 tons of corn in September 2014. The contract size for corn futures is 127 tons, so the farmer will enter short position in 1,575 futures contracts for corn with settlement day in September 2014. (He wants to sell the corn for a given price in September 2014.)

But this matching of both the underlying assets and dates is very rare, so companies often enter a position in a futures contract on correlated assets or with a settlement day close to the desired settlement day. This problem is described by Witzany (2011). If the maturity of a future is longer than the desired maturity then there is time basis risk. If we want to sell an asset at time T_1 which is earlier than maturity of the future T_2 we can enter the short position in the contract and close it at time T_1, and then we will sell the asset for the spot price S_1 and make a gain from the futures $(F_0 - F_1)$, where F_i is futures price at time i. Analogously, if the futures price decreases, a seller in a contract gains in a similar manner.

The seller has: $S_1+(F_0-F_1) = F_0+(S_1-F_1)$, where the difference S_1-F_1 is called the basis and it is not necessary equal to zero before maturity; however, the risk is negligible, as spot price and futures price converge at the time of settlement, see Figure 2.1.

The risk increases if there is a difference in the underlying assets as well; then we can only assume a positive correlation in the prices. In our study, we focus on this type of the problem. We try to minimize the risk of changes in spot prices. We assume a case when a company owns N units of an asset and

Figure 2.2: Variance in spot returns vs. variance of hedged portfolio (naive hedging)



wants to fix their future value. The current value of the asset is $V_0 = N \cdot S_0$ and without hedging the future value would be $V_T = N \cdot S_T$ at time T. We assume that there is positive correlation between the changes in spot price of the assets ($\Delta S = S_T - S_0$) and futures price of a contract on a related asset ($\Delta F = F_T - F_0$), so the company enters into the short position in a futures contract. If the spot price decreases, the futures price decreases as well. The company diminishes the loss from the decrease in spot price by the gain from the futures contract. The change in the portfolio's value is $\Delta V = N \cdot \Delta S - M \cdot \Delta F$, where M is the number of entered futures. The main question is how many futures contract we should use to minimize the risk. In other words, how M should be determined to minimize fluctuation in the portfolio's value. The futures position should correspond to $h \cdot N$ units of underlying assets, where h is an unknown coefficient called “hedge ratio” and $h = M/N$. Hedging can significantly diminish the risk of spot position defined by variance in returns as depicted in Figure 2.2. Too small hedge ratio does not cover risks corresponding to the asset ownership, too high hedge ratio, on the other hand, opens a new risky position in the underlying asset. We deal with estimation of optimal hedge ratio in the following sections.

Chapter 3

Types of hedge ratios and literature overview

Determination of optimal hedge ratio depends on the objective function that is optimized and different authors take various approaches to its definition. One of the widely-used strategies is to minimize variance (risk) of the portfolio with so called minimum variance hedge ratio; this approach is easy to understand and implement but it ignores the expected return of the hedged portfolio. Hence, many other hedge ratios have been proposed recently; we can name, for example, mean-variance hedge ratio, hedge ratio derived from maximization of expected utility or minimizing of the mean extended-Gini coefficient, and generalized semivariance-based hedge ratio. All of the models ignore transaction costs and investment in other securities than futures. Another attribute distinguishing the approaches is the dynamic nature of hedge ratio. Some studies consider static hedge ratio and use unconditional probability distribution for estimation, other studies allow hedge ratio to vary over time employing ARCH and GARCH models. In the following sections, we describe the chosen methods for derivation of hedge ratios and results of studies employing these methods.

3.1 Definition of hedge ratio

Hedge ratio can be established using either price changes (profits) or return of portfolio. Portfolio value is defined as summation of values of all assets belonging to the portfolio, in our case we are restricted to a portfolio consisting of M units in futures contracts and N spot asset's units. Change in the portfolio value over one time unit t is defined as $\Delta V_t = N \cdot \Delta S_t - M \cdot \Delta F_t$ and related hedge ratio is $h = M/N$ as explained in Chapter 2; $\Delta S_t = S_t - S_{t-1}$ and $\Delta F_t = F_t - F_{t-1}$.

Return on portfolio is given by $R_{pt} = \frac{NS_tR_{st} - MF_tR_{ft}}{NS_t}$ where $R_{s,t+1} = \frac{(S_{t+1}-S_t)}{S_t}$ and $R_{f,t+1} = \frac{(F_{t+1}-F_t)}{F_t}$ are returns on spot asset and futures contract, respectively. The hedge ratio is then defined as $H = MF_t/NS_t$ and return on portfolio can be rewritten to $R_{pt} = R_{st} - HR_{ft}$.

3.2 Minimum variance hedge ratio (MV)

The MV hedge ratio belongs among static hedge ratios which remain constant over time. The hedge ratio was derived by Johnson (1960) and the derivation is based on minimization of risk defined as variance in the value of the hedged portfolio. Using hedge ratio defined in the terms of price changes, we get the variance in changes given by the following equation:

$$Var(\Delta V_t) = N^2 Var(\Delta S_t) + M^2 Var(\Delta F_t) - 2NMCov(\Delta S, \Delta F). \tag{3.1}$$

To get the hedge ratio, we have to derive the equation according to the number of futures and set the derivation equal to 0:

$$2MVar(\Delta F_t) - 2NCov(\Delta S, \Delta F) = 0 \tag{3.2}$$

From the previous section we know that $h = M/N$, so we get

$$h = M/N = \frac{Cov(\Delta S, \Delta F)}{Var(\Delta S_t)}. \tag{3.3}$$

Alternatively, for the revenues-based hedge ratio, H, we have

$$Var(R_p) = Var(R_s) + H^2 Var(R_f) - 2HCov(R_s, R_f) \tag{3.4}$$

and

$$H = \frac{Cov(R_s, R_f)}{Var(R_f)}. \tag{3.5}$$

The MV hedge ratio is very simple and easy to understand, but it focuses on risk of portfolio and ignores expected return. As expected return is disregarded, the MV hedge ratio is the same as the mean-variance hedge ratio only in case of infinitely risk averse investors or zero expected return on futures contracts.

The minimum variance hedge ratio can be modified to dynamic hedge ratio by making it dependent on conditional or current information. The hedge ratio is then given by $h|\Omega_t = \frac{M}{N} = \frac{Cov(\Delta S,\Delta F)|\Omega_{t-1}}{Var(\Delta F)|\Omega_{t-1}}$.

There are several approaches for estimation of the minimum variance hedge ratio such as OLS method, GARCH method, or cointegration and error correction methods. Detailed description of methods used in this study can be found in Chapter 4.

The MV method is greatly covered in existing literature.

3.2.1 Literature overview

Ederington (1979) and Myers and Thompson (1989) use the OLS method in their studies, regressing changes of spot prices on changes of futures prices, the coefficient of futures prices is an estimator of hedge ratio. Ederington employs the price changes hedge ratio and examines the hedge ratios for GNMA's, Treasury Bills, Wheat and Corn in years 1976-1977. The author operates with nearby contracts and the hedging period of 2 and 4 weeks and he finds that the hedge ratio approaches 1 with increasing length of the hedging period. Further, he examines the hedging effectiveness defined as

$$e = 1 - \frac{Var(R_p)}{Var(R_s)}; \tag{3.6}$$

hedging effectiveness increases with length of hedging period as well. While the estimated hedge ratios for GNMA's, Wheat and Corn take values between 0.75 and 0.95 in case of 2 weeks hedging and between 0.84 and 1.05 for 4 weeks hedging, the hedge ratio for Treasury Bills is much lower, acquiring values between 0.11 and 0.31 for 2 weeks hedge and 0.22 and 0.65 for 4 weeks hedge.

Myers and Thompson (1989) examine several OLS approaches for estimation of hedge ratio. Specifically, they employ the simple OLS regression in levels, price changes, and returns. They point out some drawbacks of each of the estimators and suggest using a generalized approach regressing (changes in) spot price on (changes in) futures prices and some other information known at time $t-1$ (e.g. lags of the prices), marking the coefficient of futures prices as estimators of the hedge ratio. They study the hedge ratios of Wheat, Soybeans and Corn in Michigan and assume that the hedging period is one week. The estimated hedge ratio varies according to the used method. Myers and Thompson use the generalized approach to evaluate the estimators gained by OLS with levels, changes, and returns and find that OLS with changes in prices gives results closest to the generalized approach. Their hedge ratios based on the generalized approach take values of 0.85 for Corn, 1.02 for Soybeans and 0.94 for Wheat.

The cointegration and error correction method is used together with either OLS regressions or GARCH regressions. Kenourgios et al. (2008) compare several methods of hedge ratio estimators including the error correction model. Other authors using the error correction models are e.g. Lien and Luo (1993a) and Chou et al. (1997). Papers using error correction in GARCH models are discussed later.

Lien and Luo (1993a) examine multi period hedge ratios for foreign currencies and stock indices, the hedge period is assumed to be one week, and the nearby futures are employed. They find that spot and futures prices are cointegrated and the multi period hedge ratio exhibits cyclical patterns with declining amplitude of the cycles. All of the estimated hedge ratios are very close to one (not smaller than 0.83 and not larger than 1.01).

Chou et al. (1997) study the error correction model using Nikkei stock index and find that the model outperforms the conventional OLS model with price changes in the reduction of the cash position risk. The improvement with the error correction model averages about 2%. The authors use different time intervals - from daily to 5-week intervals - and the hedge ratio increases with the length of the intervals. The conventional hedge ratios vary between 0.75 and 1.01 for different time intervals and the error correction hedge ratios take values between 0.76 and 0.99 for different time intervals.

Kenourgios et al. (2008) estimate hedge ratio using four different models - conventional OLS, error correction, GARCH, and EGARCH. They examine the hedge ratio of S&P500 stock index on weekly basis and find that the error correction model provides better risk reduction than any other model. However, all the estimated hedge ratios are very close, taking values between 0.945 and 0.958.

The GARCH model is employed by e.g. Baillie and Myers (1991), Park and Switzer (1995), or Park and Jei (2010). Baillie and Myers use the bivariate GARCH(1,1) model; they examine the hedge ratios of six commodities - Beef, Coffee, Corn, Cotton, Gold, and Soybeans, using daily data. The hedge ratios are estimated based on the conditional variance-covariance matrix, so the study results in time-varying hedge ratios. The authors find that the hedge ratios follow a unit root process. The in-sample and out-of-sample comparison of the

GARCH-based hedge ratio and constant hedge ratios shows that the GARCH-based hedge ratio is significantly better.

Park and Switzer (1995) employ the bivariate GARCH(1,1) model for estimation of the hedge ratios for stock indices and compare the results with results of unhedged portfolio, naive hedging, OLS hedge ratio, and OLS with error correction term hedge ratio. The hedging period is one week. The results show that the GARCH estimators noticeably improve the hedging effectiveness compared to the other three named methods.

Park and Jei (2010) try to adopt more flexible bivariate density functions, as they consider asymmetric individual conditional variance equations and incorporate asymmetry in the conditional correlation equation for the dynamic conditional correlation GARCH model. They examine the results based on reduction in returns variance and Value at Risk, using daily data on Corn and Soybeans. The authors discover that asymmetric and flexible density specifications increase the goodness-of-fit but do not guarantee better hedging performance. Further, they find an inverse relationship between the variance of hedge ratios and the hedging effectiveness.

Kroner and Sultan (1993) use the bivariate error correction model with GARCH error to estimate the hedge ratios of five currencies, weekly data. The in-sample and out-of-sample analyses show that the proposed hedging strategy is superior to the other conventional strategies.

3.3 Optimum mean-variance hedge ratio

The mean variance framework incorporates both risk and return into the derivation of optimal hedge ratio, but function used for the optimization is not strictly defined. For example, Hsln et al. (1994) propose to maximize the following expected utility function for derivation of the optimal hedge ratio:

$$max_M V(E(R_p), \sigma_p; A) = E(R_p) - 0.5A\sigma_p^2, \tag{3.7}$$

where A stands for risk aversion, σ_p for standard error of portfolio's revenues, and σ_p^2 for variance of the portfolio's revenues. Hsln et al. (1994) assume exponential utility function and normal returns, which reduce expected the utility maximization approach to the mean variance analysis with linear, additive function. They then derive the hedge ratio from the first order condition of the equation, obtaining

$$H = -\left[\frac{E(R_f)}{A\sigma_f^2} - \rho\frac{\sigma_s}{\sigma_f}\right], \tag{3.8}$$

where ρ denotes correlation coefficient of the returns on the spot and futures positions and σ_s,σ_f stand for the returns on the spot and futures positions, respectively. A drawback of this method is the necessity of individual's aversion parameter knowledge for derivation of the optimal hedge ratio; further, different people would choose different hedge ratios based on their specific aversion to risk.

We can derive the conditions for equality of the MV hedge ratio and the mean-variance ratio from Equation 3.8. The returns-based MV hedge ratio can be rewritten using the correlation coefficient:

$$H = \frac{Cov(R_s, R_f)}{Var(R_f)} = \frac{\rho\sigma_s\sigma_f}{\sigma_f^2} = \frac{\rho\sigma_s}{\sigma_f,} \tag{3.9}$$

which corresponds to the second part of the mean-variance-based hedge ratio equation, and we can confirm that these two ratios are equal if and only if investors are infinitely risk averse ($A \longrightarrow \infty$) or the expected return on the portfolio is zero ($E(R_f) = 0$). The second condition is fulfilled if the futures prices follow a simple martingale process. Some of the hedge ratios described below can be labelled as mean variance hedge ratios as well.

Hsln et al. (1994) use daily currencies data and the hedging horizon of 14, 30, 60, 90, and 120 days. The authors compare the hedging effectiveness of hedging with futures, and options and the results indicate that futures are a better hedging tool.

3.4 Sharpe hedge ratio

Sharpe ratio is a tool for examination of investment performance by adjusting for risk developed by Sharpe (1966). It measures risk premium or excess return per unit of deviation in investment, and Sharpe originally called it the "reward for variability" ratio. Sharpe ratio was firstly defined as $S = \frac{E(R_p)-r}{\sigma_p}$, where r stands for the risk-free interest rate. $E(R_p)$ and σ_p represent expected return of portfolio and standard deviation of the portfolio's returns, respectively.

Howard and D'Antonio (1984) argue that the optimal level of future contracts can be obtained by maximizing Sharpe ratio as defined above:

$$max_M \theta = \frac{E(R_p) - r}{\sigma_p}. \tag{3.10}$$

This leads to the optimal number of futures given by:

$$M = -N \frac{(S/F)(\sigma_s/\sigma_f)[(\sigma_s/\sigma_f)(E(R_f)/(E(R_s) - r)) - \rho]}{[1 - (\sigma_s/\sigma_f)(E(R_f)\rho/(E(R_s) - r))]}. \tag{3.11}$$

And the optimal hedge ratio can be written as

$$H = -\frac{(\sigma_s/\sigma_f)[(\sigma_s/\sigma_f)(E(R_f)/(E(R_s) - r)) - \rho]}{[1 - (\sigma_s/\sigma_f)(E(R_f)\rho/(E(R_s) - r))]}. \tag{3.12}$$

Again, in case of zero expected return on futures ($E(R_f) = 0$) we get $H = \rho\frac{\sigma_s}{\sigma_f}$, which is equal to the MV hedge ratio. The advantage of the Sharpe index-based hedge ratio is that it does not explicitly incorporate the risk-aversion parameter. However, Chen et al. (2001) highlight also some downsides of this type of hedge ratio; Sharpe ratio is non-linear function of hedge ratio, and the second order condition has to be checked to ensure maximum Sharpe ratio. Further they show some examples of undefined optimal hedge ratio; in these cases, Sharpe ratio monotonically increases with hedge ratio.

The Sharpe hedge ratio is covered in study by De Jong et al. (1997) who compares hedge ratios based on minimum variance, generalized semivariance and Sharpe hedge ratio using currencies futures. The paper finds that the naive hedge ratio outperforms the other hedge ratios.

3.5 Maximum expected utility hedge ratio

Another principle that takes into account both risk and return is the expected utility maximization principle. The above mention types of hedge ratios incorporating both risk and return are consistent with the mean-variance framework; however, the consistency with the expected utility maximization principle is ensured only under special conditions. These are quadratic utility function and jointly normally distributed returns. To make the hedge ratio consistent with the expected utility maximization principle, some authors focus on maximization of expected utility. The utility function varies among studies on this topic; for instance, Cecchetti et al. (1988) assume the utility function to be logarithm of terminal wealth. Their hedge ratio maximizes the following function:

$$\int \log[1 + R_s - HR_f]f(R_s, R_f)dR_s dR_F, \tag{3.13}$$

where $f(R_s, R_f)$ is bivariate normal density function.

Cecchetti et al. use the third-order linear bivariate ARCH model to get the conditional variance-covariance matrix and then employ numerical maximization of the objective function with respect to the hedge ratio. They examine monthly data on Treasury bonds. The hedge ratio varies over a sizeable range, from 0.52 to over 0.91, depending on expectations about risk and return.

3.6 Minimum mean extended-Gini coefficient hedge ratio (MEG)

The usage of mean extended-Gini coefficient in construction of optimal portfolio was firstly proposed by Shalit and Yitzhaki (1984), and they mark it as a workable alternative to the classical Markowitz's mean-variance CAMP. The mean extended-Gini coefficient is defined as:

$$\Gamma_\upsilon(R_p) = -\upsilon Cov(R_p, (1 - G(R_p))^{\upsilon - 1}), \tag{3.14}$$

where G is cumulative probability distribution and υ stands for the risk aversion parameter; the hedge ratio is based on minimization of $\Gamma_\upsilon(R_p)$. We may divide investors into three categories according to the υ parameter: risk seekers have υ between 0 and 1, υ of risk neutral investors is equal to 1, and υ bigger than 1 implies risk aversion. The cumulative probability distribution, G, is usually unknown and has to be estimated empirically. Two approaches for calculation of the MEG hedge ratio are presented in Chapter 4.

Shalit (1995) proves that the minimum MEG hedge ratio is equal to the MV hedge ratio under the condition of jointly normally distributed futures and spot returns. He studies dependence of the hedge ratio on the value of risk parameter and finds that the relationship differs for various types of underlying assets, especially for small values of the risk parameter. In most of the cases, the hedge ratio starts to increase with the increasing risk parameters at some point, but there are some exceptions.

3.6.1 Literature overview

This approach is widely used and can be found in papers by Kolb and Okunev (1992), Lien and Shaffer (1999), and others. Cheung et al. (1990) use the mean-Gini coefficient in their paper. Kolb and Okunev (1993) propose incorporation of the mean extended-Gini coefficient to utility function in order to take the expected return into account as well. They maximize the following utility function: $U(R_p) = E(R_p) - \Gamma_\upsilon(R_p)$. This hedge ratio is denoted as the M-MEG hedge ratio. If future prices follow a martingale process and the expected return is equal to 0, the two hedge ratios are equal.

Lien and Luo (1993b) use stock index futures with weekly hedge period and find that the MEG hedge ratio approaches the MV hedge ratio for $\upsilon = 9$, and the hedge ratio converges to a constant for large υ . The results indicate that the hedge ratio decreases with the risk aversion parameter υ. The MEG hedge ratio for low υ parameter is more stable than the hedge ratio for large υ.

Lien and Shaffer (1999) estimate the MEG hedge ratio based on the instrumental variable method used by Shalit (1995) and calculate the true MEG hedge ratio using the cumulative probability distribution. The authors use daily stock index data and find that the MEG hedge ratio obtained through the instrumental variable method is different than the true hedge ratio.

Kolb and Okunev (1992) examine the hedge ratios for Corn, Copper, Gold, German mark, and S&P 500 index on daily basis. The risk aversion parameter, υ, varies from 2 to 200. The paper finds that the MEG hedge ratio is close to the MV hedge ratio for low υ, but the two hedge ratios are significantly different for higher values of υ. The changes in the hedge ratio with increasing υ vary for different types of commodities. The hedge ratio is more stable for larger υ.

3.7 Minimum generalized semivariance hedge ratio (GSV)

Definition of risk as a variance in prices is very conservative as it considers all extremes (positive and negative) to be undesirable. Besides, the mean-variance analysis is reliable only under the following restrictions: quadratic utility function or normal distribution of returns with negative exponential utility function. The semivariance analysis was proposed to overcome the limitation of the mean-variance analysis. The main advantage of semivariance minimization is its focus on the reduction of losses. The concept was firstly presented by Markowitz (1959) and then developed by Mao (1970), who uses the lower partial moments of the assets distribution. Fishburn (1977), Bawa (1978), and Harlow and Rao (1989) develop a generalized semivariance-based risk-return model which forms the basis for the general semivariance hedge ratio research.

Fishburn formulates $\alpha - t$ model where he describes the expected disutility of outcome lower than the target return, t, weighted by the measure for risk aversion, α. The risk is defined by the two-parameter function:

$$G_{\alpha,\delta}(R_{p,b}) = \int_{-\infty}^{\delta} (\delta - R_{p,b})^{\alpha} dF(R_{p,b}), \tag{3.15}$$

where $G_{\alpha,\delta}(R_{p,b})$ stands for expected utility of loss, δ is the target return, α measures risk aversion for below-target returns, $R_{p,b}$ is the below-target return, and $F(R_{p,b})$ is probability distribution function of the below-target return in a hedged portfolio. The GSV hedge ratio is obtained by minimizing $G_{\alpha,\delta}(R_p)$.

Again, we can divide investors into three categories according to the α parameter: α between 0 and 1 denotes a risk seeking individual, α equal to 1 stands for a risk neutral individual, and α larger than one corresponds to risk averse investors. Bawa (1978) and Fishburn (1977) show that GSV is consistent with the concept of stochastic dominance, but Chen et al. (2001) argue that the stochastic dominance consistency of GSV does not imply the stochastic dominance of the GSV hedge ratio. The consistency is conditioned by independence of the hedge ratio on the target return. The GSV hedge ratios usually differ for various target returns, the independence condition is thus not satisfied, and the GSV hedge ratio is not necessarily consistent with the stochastic dominance concept. Lien and Tse (1998) prove that the GSV hedge ratio and the MV hedge ratio are identical under conditions of jointly normal distribution of futures and spot returns and future prices following a pure martingale process. The GSV hedge ratio is another representative of static hedge ratios.

The hedge ratio can be extended to the M-GSV hedge ratio where the optimal hedge ratio maximizes the following risk-return function

$$U(R_p) = E(R_p) - G_{\alpha}(t, R_p). \tag{3.16}$$

This approach is proposed in the paper by Chen et al. (2001).

Chen et al. use weekly stock index data and estimate several types of hedge ratios including the minimum generalized semivariance hedge ratio, which is extended to the mean-returns hedge ratio in the paper. They find that the mean-return generalized semivariance hedge ratio varies less than the minimum generalized semivariance hedge ratio for lower and relevant levels of risk aversion. The mean-return generalized semivariance hedge ratio converges to higher values than the minimum variance hedge ratio for large values of risk aversion.

3.8 Minimum Value at Risk hedge ratio (VaR)

The minimum variance approach ignores higher moments of return distribution, and it can increase negative skewness or kurtosis of hedge portfolio returns. To avoid this problem, Harris and Shen (2006) suggest using of the minimum Value at Risk and minimum conditional Value at Risk hedge ratios, estimated non-parametrically using historical simulations. The Value at Risk is defined as the largest loss on portfolio that can be expected with a given probability over a certain time horizon and was firstly outlined in the “safety-first” criterion by Roy (1952).

Harris and Shen suppose that a portfolio consist of two assets - the short position in the second asset is used to hedge the long position in the first asset - which corresponds to our model of the long position in spot market and the short position in futures market, so we can mark the per-period returns as R_s and R_f. They assume that the mean returns for both assets are zero.

The return of hedged portfolio is given by

$$R_p = R_s - HR_f. \tag{3.17}$$

The variance of hedged portfolio return is defined as

$$\sigma_p^2 = var(R_s - HR_f) = \sigma_s^2 + H^2\sigma_f^2 - 2H\rho_{s,f}\sigma_s\sigma_f, \tag{3.18}$$

where σ_s^2 and σ_f^2 are variances of R_s and R_f, respectively, and $\rho_{s,f}$ is correlation between R_s and R_f.

The skewness of hedged portfolio is given by

$$s_p = \frac{E[R_p^3]}{\sigma_p^3} = \frac{s_s\sigma_s^3 - 3Hs_a\sigma_s^2\sigma_f + 3H^2s_b\sigma_s\sigma_f^2 - H^3s_f\sigma_f^3}{(\sigma_s^2 + H^2\sigma_f^2 - 2H\rho_{s,f}\sigma_s\sigma_f)^{3/2}}, \tag{3.19}$$

where the skewness and co-skewness coefficients can be written as $s_s = \frac{E[R_s^3]}{\sigma_s^3}$, $s_f = \frac{E[R_f^3]}{\sigma_f^3}$, $s_a = \frac{E[R_s^2 R_f]}{\sigma_s^2 \sigma_f}$, and $s_b = \frac{E[R_s R_f^2]}{\sigma_s \sigma_f^2}$.

And the kurtosis coefficient is given by

$$k_p = \frac{E[R_p^4]}{\sigma_p^4} = \frac{k_s\sigma_s^4 - 4Hk_a\sigma_s^3\sigma_f + 6H^2k_b\sigma_s^2\sigma_f^2 - 4H^3k_c\sigma_s\sigma_f^3 + H^4 s_f \sigma_f^4}{(\sigma_s^2 + H^2\sigma_f^2 - 2H\rho_{s,f}\sigma_s\sigma_f)^2}, \tag{3.20}$$

where the kurtosis and co-kurtosis coefficients are defined as $k_s = \frac{E[R_s^4]}{\sigma_s^4}$, $k_f = \frac{E[R_f^4]}{\sigma_f^4}$, $k_a = \frac{E[R_s^3 R_f]}{\sigma_s^3 \sigma_f}$, $k_b = \frac{E[R_s^2 R_f^2]}{\sigma_s^2 \sigma_f^2}$, and$k_c = \frac{E[R_s R_f^4]}{\sigma_s \sigma_f^4}$.

If we suppose that our returns are zero, the Value at Risk of a portfolio can be written as:[1]

$$VaR_p = -\sigma_p q_p^\alpha(s_p, k_p), \tag{3.21}$$

where q_p^α denotes α percent quantile of the standardised distribution of hedged portfolio returns, and α is equal to one minus the VaR confidence level. In case of normally distributed returns, s_p is equal to 0, k_p is equal to 3, and VaR is a constant multiple of the standard deviation of returns. Reduction in skewness and growth in kurtosis increase the VaR of portfolio returns for high VaR confidence levels.

Harris and Shen (2006) empirically show that the minimum VaR and C-VaR hedge ratios generate out-of-sample improvements in the VaR and C-VaR of hedged portfolio compared to the minimum-variance hedging.

Cao et al. (2010) argue that the non-parametric approach relies on a large historical sample of spot and futures prices data and it is unable to capture the time-varying nature of the hedge ratio; hence, they suggest a semi-parametric approach based on the Cornish and Fisher (1937) expansion approximating quantile q_p^α using higher moments of the distributions of hedge portfolio returns. For skewness and kurtosis of the return distribution, the Cornish-Fisher expansion approximates q_p^α by

$$\tilde{q_p^\alpha}(s_p, l_p) = c(\alpha) + \frac{1}{6}[c(\alpha)^2 - 1]s_p + \frac{1}{24}[c(\alpha)^3 - 3c(\alpha)](k_p - 3) - \frac{1}{36}[2c(\alpha)^3 - 5c(\alpha)]s_p^2, \tag{3.22}$$

where $c(\alpha)$ is the α percent quantile of the standard normal distribution.[2] The

[1] The mean spot and futures returns of our commodities are very close to zero, so we can use this assumption. Further, it is a common assumption when dealing with daily financial asset returns.

[2] The number $c(\alpha)$ is negative.

Cornish-Fisher approximation for the VaR of the hedge portfolio is then given by

$$VaR_p = -\sigma_p \tilde{q_p^{\alpha}}(s_p, k_p). \tag{3.23}$$

To obtain the minimum-VaR hedge ratio, Cao et al. (2010) differentiate Equation 3.23 with respect to the hedge ratio, H, and set the first derivative equal to zero getting the following first-order condition:

$$\frac{\partial \sigma_p}{\partial H}(A_1 + A_2 s_p + A_3 k_p 1 A_4 s_p^2) + \sigma_p(A_2 \frac{\partial s_p}{\partial H} + A_3 \frac{\partial k_p}{\partial H} + 2A_4 s_p \frac{\partial s_p}{\partial H}) = 0, \tag{3.24}$$

where $A_1 = c(\alpha) - \frac{1}{8}[c(\alpha)^3 - 3c(\alpha)]$, $A_2 = \frac{1}{6}[c(\alpha)^2 - 1]$, $A_3 = \frac{1}{24}[c(\alpha)^3 - 3c(\alpha)]$, and $A_4 = \frac{1}{36}[2c(\alpha)^3 - 5c(\alpha)]$.

Harris and Shen (2006) employ daily data for foreign currencies and find that the minimum-variance hedging substantially increases portfolio's kurtosis, so the reduction in VaR is lower than the reduction in standard deviation; the VaR of the minimum-VaR portfolio is by fifteen percent lower than the VaR of the minimum-variance hedge portfolio. Further, the results show that the minimum VaR hedge ratios are typically considerably smaller than the minimum-variance hedge ratios. The differences in variance reduction are not significant.

Cao et al. (2010) employ daily stock indices data and use the semi-parametric method of minimum-VaR and minimum-CVaR hedge ratios estimation based on the Cornish-Fisher expansion. They find that the semi-parametric approach is superior to the non-parametric approach by Harris and Shen (2006) because it provides a larger reduction in negative skewness and excess kurtosis, so the hedged portfolios have lower VaR.

3.9 Dynamic hedge ratio

Because keeping hedge ratio static over time may not be the optimal approach of hedging, we present two ways of dynamic hedging. The first approach recalculates hedge ratio based on current covariance of spot and future prices (σ_{sf}) and variance of future prices (σ_f^2). The MV hedge ratio is then calculated based on conditional information: $h_1|\Omega_{t-1} = \frac{\sigma_{sf}|\Omega_{t-1}}{\sigma_f^2|\Omega_{t-1}}$.

Lien and Luo (1993) propose a multi-period model instead. They minimize variance of wealth at the end of T periods planning horizon, W_T. N_t stands for the spot position at the beginning of period t, M_t denotes the futures position at the beginning of period t, and $M_t = -h_t N_t$ holds, h_t is the hedge ratio. The wealth at the end of planning horizon is

$$W_T = W_0 + \sum_{t=0}^{T-1} N[S_{t+1} - S_t - h_t(F_{t+1} - F_t)] = W_0 + \sum_{t=0}^{T-1} N[\Delta S_{t+1} - h_t \Delta(F_{t+1})]. \tag{3.25}$$

The optimal hedge ratio h_t is given as:

$$h_t = -\frac{Cov(\Delta S_{t+1}, \Delta F_{t+1})}{Var(\Delta F_{t+1})} - \sum_{t=i+1}^{T-1} \frac{N_i}{N_t} \frac{Cov(\Delta F_{t+1}, \Delta S_{i+1} + h_i \Delta F_{i+1})}{Var(\Delta F_{t+1})}. \tag{3.26}$$

The correlation of changes in current prices and changes in futures prices or future spot prices implies a difference between the multi-period and single-period hedge ratios.

Chapter 4

Estimation of the optimal hedge ratio

We estimate several types of hedge ratio and compare the results with unhedged portfolio and the naive hedge. Specifically, we focus on minimum variance hedge ratio based on OLS model, error correction model, GARCH model, GARCH model with error correction and bivariate GARCH model, Sharpe hedge ratio, MEG hedge ratio, GSV hedge ratio and minimum-VaR hedge ratio. The estimation methodology for each hedge ratio is described in details in this section.

4.1 Estimation of the MV hedge ratio

There are several approaches used for estimation of the MV hedge ratio including several OLS methods and GARCH methods allowing the hedge ratio to change over time. We start the analysis investigation of studying individual series to find the order of the series and to detect possible autocorrelation.

We identify the series order using Augmented Dickey Fuller test employing the following regression to detect the non-stationarity:

$$\Delta y_t = \alpha + \beta t + \gamma y_{t-1} + \delta_1 \Delta y_{t-1} + ... + \delta_{p-1} \Delta y_{t-p+1} + \epsilon_t, \tag{4.1}$$

where α stands for constant, β is coefficient of time trend and p is lag order of autoregressive process. If $\alpha = 0$ and $\beta = 0$, the equation corresponds to random walk modelling. The number of lags is influenced by the autocorrelation structure of variables.

If a series is integrated of order one, we have to use its differences to make it stationary as regressing non-stationary time series may lead to spurious regression showing a relationship between series that does not exists and shows up only because of the common trend. All spot and futures prices time series we use are integrated of order one, so we must set all regressions in differences.

4.1.1 OLS method

The price-change hedge ratio is defined as the ratio between covariance of spot and futures price changes and variance of futures price change. To implement this rule, it is necessary to estimate the relevant covariance and variance from the available data first. The conventional approach of the hedge ratio estimation uses ordinary least square regression of changes in spot prices on changes in futures prices presented for example in Junkus and Lee (1985) or Carter and Loyns (1985). Some researchers also regress levels or returns of spot prices on levels or returns of futures prices (Ederington 1979 and Brown 1985, respectively). Myers and Thompson (1989) argue that the regression of level prices is based on a very unrealistic assumption that equilibrium prices equal constant plus a serially uncorrelated shock. Further, Myers and Thompson claim that the regression with returns implies conditional covariance matrix of spot and futures price levels changing over time; a simple regression can be used only if the optimal hedge ratio does not change over time. Hence, a new, strong condition is imposed on the spot and futures prices, specifically $S_T = F_T$. Based on these arguments, the regression with price changes is the most realistic one.

The regression of price changes can be written down as

$$\Delta S_t = \alpha_0 + \alpha_1 \Delta F_t + \epsilon_t \tag{4.2}$$

and the hedge ratio based on price changes, h, is given by the coefficient α_1. The validity and efficiency of the OLS technique is conditioned by satisfying the OLS assumptions: correct specification of the linear function, zero condition mean of error ϵ, no perfect collinearity among the independent variables or sample variation in the independent variable in case of one independent variable model, homoskedasticity, no serial autocorrelation in errors, and normally distributed unobserved error.

The first three assumptions ensure unbiasedness of OLS estimates; under the assumptions one to five (Gauss-Markov assumptions) OLS is the best linear unbiased estimator; under assumptions one to six, OLS estimates are normally distributed, conditional on independent variables, and the usual construction of confidence intervals is valid. The assumption of heteroskedasticity is often violated; the problem is solved by ARCH and GARCH models described in the following subsection.

Myers and Thompson (1989) point out that the OLS method uses unconditional sample moments instead conditional ones. They propose to use conditional variance and covariance using currently available information in the optimal hedge ratio calculation:

$$h = \frac{M}{N} = \frac{Cov(\Delta S, \Delta F)|\Omega_{t-1}}{Var(\Delta F)|\Omega_{t-1}}, \tag{4.3}$$

where Ω_{t-1} denotes the current information including vector of variables X_{t-1} known at $t-1$.
Changes in spot and futures prices are described by the following equilibrium model

$$\Delta S_t = \alpha_0 X_{t-1} + u_t \text{ and } \Delta F_t = \beta_0 X_{t-1} + v_t, \tag{4.4}$$

u_t and v_t are stochastic shocks with zero mean and no serial correlation conditional on X_t.

Myers and Thompson set the hedge ratio equal to the ratio of the estimated condition covariance between spot and futures prices and the estimated condition variance of the futures prices; they show that the conditional covariance matrix of spot and futures prices is equal to the covariance matrix of the residuals, u_t and v_t, so the hedge ratio is given by the following equation:

$$\widehat{h}|X_{t-1} = \frac{\widehat{Cov}(u_t, v_t|X_{t-1})}{\widehat{Var}(v_t|X_{t-1})}. \tag{4.5}$$

In general, the hedge ratio obtained through the Equation 4.5 is different than the hedge ratio given by Equation 3.3, the two hedge ratios equal under a condition of spot and futures prices following random walk:

$$\Delta S_t = \alpha_0 + u_t \text{ and } \Delta F_t = \beta_0 + v_t. \tag{4.6}$$

If this condition does not hold, the OLS hedge ratio is not optimal.

Myers and Thompson suggest to use a single-equation approach to the generalized optimal hedge ratio estimation motivated by the proposition that the generalized optimal hedge ratio estimator is equal to the OLS estimate of γ

under conditions described in Equation 4.6:

$$\Delta S_t = \gamma \Delta F_t + \alpha X_{t-1} + \epsilon_t. \tag{4.7}$$

The equation is called "augmented reduced form". Further, the authors assume that X_{t-1} contains only a constant and lags, but they do not specify the number of lags that should be used. To find the optimal number of lags, we estimate several types of the model and use Adjusted R^2 and information criteria (Akaike and Bayesian) to evaluate the models. We estimate two hedge ratios using the simple OLS model: using the basic model and the best model according to the criteria, and we compare the results. Theoretically, the more specified model should provide more efficient hedge ratio as better describe the data.

4.1.2 Cointegration and error correction model

If two time series contain a unit root, it is possible that the series are cointegrated, and we need to estimate the error-correction model. It is now well known that spot and futures prices are non-stationary and the cointegration relationship plays an important role in the statistical modelling of the prices (Lien and Luo 1993b; Ghosh 1993; Wahab and Lashgari 1993; Tse 1995).

The cointegration model was developed by Engle and Granger (1987). ΔS_t and ΔF_t denote continuously compounded (log) returns of spot a futures prices. Suppose that both spot and futures prices are integrated of order one and the returns are thus stationary. The series are cointegrated if their linear combination is stationary; in other words, if there exist a coefficient β such that $S_t = \beta F_t + u_t$ where $u_t \sim I(0)$. The error correction model can be specified as

$$\Delta S_t = \alpha_s + \sum_{i=1}^{m} \beta_{si} \Delta S_{t-i} + \sum_{j=1}^{n} \gamma sj \Delta F_{t-j} + \theta_s z_{t-1} + \epsilon_{st}, \tag{4.8}$$

$$\Delta F_t = \alpha_f + \sum_{i=1}^{k} \beta_{fi} \Delta S_{t-i} + \sum_{j=1}^{l} \gamma fj \Delta F_{t-j} + \theta_f z_{t-1} + \epsilon_{ft}, \tag{4.9}$$

where $z_{t-1} =$ is a stationary linear combination of S_t and F_t.

Myers and Thompson (1989) suggest to use the following model

$$\Delta S_t = \alpha_s + \lambda \Delta F_t \sum_{i=1}^{m} \beta_{si} \Delta S_{t-i} + \sum_{j=1}^{n} \gamma sj \Delta F_{t-j} + \theta_s z_{t-1} + \epsilon_{st}, \tag{4.10}$$

the OLS estimate of λ is the minimum variance hedge ratio.

4.1.3 ARCH and GARCH models

The Autoregressive Conditional Heteroskedasticity (ARCH) model deals with dynamic forms of heteroskedasticity. Even if variance of errors is constant, there are other ways how heteroskedasticity can arise. The ARCH model was suggested by Engle (1982), who looks at the conditional variance of u_t given past errors; in this case the conditioning on all outcomes of independent variables is left implicit. The first order ARCH(1) model is given by the following equation:

$$E(u_t^2|u_{t-1}, u_{t-2}, \dots) = E(u_t^2|u_{t-1}) = \alpha_0 + \alpha_1 u_{t-1}^2. \tag{4.11}$$

The equation represents the conditional variance of u_t given the past u_t only if the errors are not serially correlated, $E(u_t|u_{t-1}, u_{t-2}, \dots) = 0$. The conditional variance is always positive; hence, $\alpha_0 > 0$ and $\alpha_1 >= 0$. If $\alpha_1 = 0$, there is no dynamic in the variance equation.

The ARCH(1) model can be also written as

$$u_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + v_t, \tag{4.12}$$

the conditional expected value of v_t is zero, $E(v_t|u_{t-1}, u_{t-2}, \dots) = 0$.

This expression reminds the autoregressive model of u_t^2, and the stability condition is the same as in the usual AR(1) model, $\alpha_1 < 1$. Positive α_1 implies positive autocorrelation in squared errors, even though u_t itself may not be serially correlated. According to Wooldridge (2008), the OLS assumptions one through five are not violated by serial correlation in squared errors and we can use OLS on the regression model $y_t = \beta_0 + \beta_1 z_t + u_t$. The usual heteroskedasticity-robust standard errors and test statistics are valid, yet using the ARCH model, it is possible to obtain consistent estimators of β_j that are asymptotically more efficient than the OLS estimators. Moreover, ARCH models also apply in case there are dynamics in the conditional mean. We have the following model:

$$E(y_t|z_t, y_{t-1}, z_{t-1}, y_{t-2}, \dots) = \beta_0 + \beta_1 z_t + \beta_2 y_{t-1} + \beta_3 z_{t-1}. \tag{4.13}$$

A typical approach supposes that the conditional variance of y_t is constant, but the variance could follow the ARCH model,

$$Var(y_t|z_t, y_{t-1}, z_{t-1}, y_{t-2}, \dots) = Var(u_t|z_t, y_{t-1}, z_{t-1}, y_{t-2}, \dots) = \alpha_0 + \alpha_1 u_{t-1}^2, \tag{4.14}$$

where $u_t = y_t - E(y_t|z_t, y_{t-1}, z_{t-1}, y_{t-2}, \dots)$. The model consists of two equations: Mean equation

$$y_t = \beta_0 + \beta_1 z_t + \beta_2 y_{t-1} + \beta_3 z_{t-1}, \tag{4.15}$$

and variance equation

$$Var(u_t|z_t, y_{t-1}, z_{t-1}, y_{t-2}, \dots) = E(u_t)^2 = \alpha_0 + \alpha_1 u_{t-1}^2. \tag{4.16}$$

There are more approaches to estimation of the model; either we can use equation by equation approach estimating each equation separately using OLS, or we can estimate the equations jointly using maximum likelihood estimation. In our work, we choose the latter option.

The ARCH model is not restricted to one lag in the residuals equation and sometimes large number of squared lagged residuals must be included to specify the model correctly. This problem is solved by Bollerslev (1986) who extends the ARCH model and introduces the GARCH model which allows more flexible lag structure, including lags of $E(u_t)^2$, to the right hand side of the equation, where $E(u_{t-1})^2$ is the predicted variance for the period $(t-1)$:

$$E(u_t)^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \delta_1 E(u_{t-1})^2. \tag{4.17}$$

This describes GARCH(1,1,) which can be generalized to GARCH (p,q) as

$$E(u_t)^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \alpha_2 u_{t-2}^2 + \dots + \alpha_q u_{t-q}^2 + \delta_1 E(u_{t-1})^2 + \delta_2 E(u_{t-2})^2 + \\ + \dots + \delta_p E(u_{t-p})^2. \tag{4.18}$$

Kenourgios et al. (2008) suggest to apply the GARCH(1, 1) estimation on the basic model introduced in the OLS section, i.e. the variance of regression disturbances is modelled as a linear function of lagged squared regression disturbances and conditional variance:

$$\Delta S_t = \alpha_0 + \alpha_1 \Delta F_t + \epsilon_t \text{ and } \sigma_t^2 = \gamma_0 + \gamma_1 \sigma_{t-1}^2 + \delta_1 \epsilon_{t-1}^2, \tag{4.19}$$

where σ_t^2 is variance of residuals, ϵ_t^2 is squared residual, δ_1 is ARCH parameter, γ_1 is GARCH parameter, and α_1 is estimator of the optimal hedge ratio. We enhance the model by including lags of spot and futures price differences and the error correction term, and we use the information criteria to identify the best model, again. We estimate both the simple and specified versions of the model, to find whether the specification has an influence on the hedging efficiency.

The bivariate GARCH models allow updating of hedge ratio over the hedging period. The bivariate GARCH model was firstly used by Cecchetti et al. (1988) in context of the maximum expected utility hedge ratio, and it was further developed by Baillie and Myers (1991) estimating the minimum variance hedge ratio. Baillie and Myers use the VEC-GARCH model, but we employ the CCC-GARCH (constant conditional correlation GARCH) model because the estimation using this model usually converges to a solution. That is in contrary to the other models, which often have problems with non-positive definiteness of conditional covariance matrix or do not find a solution even after thousands of iterations in our analysis, as we find out during our analysis.

The difference is that the VEC-GARCH models the conditional covariance matrix, G_t, directly, whereas the CCC-GARCH model uses an indirect approach. The CCC-GARCH model uses simple conditions to ensure positive definiteness of G_t, and the estimation is much easier than in the case of usual MGARCH models.

The variance-covariance matrix in the CCC-GARCH model is defined as follows:

$$G_t = D_t R D_t, \tag{4.20}$$

where R is constant conditional correlation matrix and $D_t = diag(\sigma_{1t}, \sigma_{2t}, \ldots, \sigma_{Nt})$. The structure of the R matrix is

$$R = \begin{bmatrix} 1 & \rho_{12} & \cdots & \rho_{1N} \\ \rho_{12} & 1 & \cdots & \rho_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ \rho_{1N} & \rho_{2N} & \cdots & 1 \end{bmatrix} \tag{4.21}$$

The dynamics can be characterized in the following way:

$$G_t = \begin{bmatrix} \sigma_{1t}^2 & \sigma_{12,t} & \cdots & \sigma_{1N,t} \\ \sigma_{12,t} & \sigma_{2t}^2 & \cdots & \sigma_{2N,t} \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_{1N,t} & \sigma_{2N,t} & \cdots & \sigma_{Nt}^2 \end{bmatrix} \tag{4.22}$$

$$\sigma_{it}^2 = \gamma_{i,0} + \gamma_{i,1}\sigma_{i,t-1}^2 + \delta_{i,1}\epsilon_{i,t-1}^2 \text{ where } i = 1, \ldots, N, \tag{4.23}$$

$$\sigma_{ij,t} = \rho_{ij}\sigma_{it}\sigma_{jt} \text{ where } i, j = 1, \ldots, n, i \neq j \tag{4.24}$$

The conditions to ensure positivity of variances and stationarity are $\gamma_{i,0} > 0$, $\gamma_{i,1} > 0$, $\delta_{i,1} > 0$, and $\sum_{j=1}^{p} \gamma_{ij,1} + \sum_{j=1}^{q} \delta_{ij,1} < 1$. Positive definiteness of the variance-covariance matrix is given by the correlation matrix and the regular requirements of positivity constraints are the same as for the GARCH model. The model can be estimated using the maximum likelihood method.

Baillie and Myers (1991) propose a hedge ratio based on the variance-covariance matrix of the following model:

$$\Delta Y_t = \mu + e_t, \tag{4.25}$$

which can be re-written as

$$\begin{bmatrix} \Delta S_t \\ \Delta F_t \end{bmatrix} = \begin{bmatrix} \mu_1 \\ \mu_2 \end{bmatrix} + \begin{bmatrix} e_{1t} \\ e_{2t} \end{bmatrix}, e_t|\Omega_{t-1} \sim N(0, G_t), \tag{4.26}$$

where G_t is conditional covariance matrix of e_t, $G_t = \begin{bmatrix} G_{11,t} & G_{12,t} \\ G_{21,t} & G_{22,t} \end{bmatrix}$, and as shown above $G_t = D_t R D_t$, $D_t = diag(\sigma_{1t}, \sigma_{2t}, \ldots, \sigma_{Nt})$ and R represents the correlation matrix. The conditional MV hedge ratio is given by

$$H_{t-1} = \frac{G_{12,t}}{G_{22,t}}. \tag{4.27}$$

As the variance-covariance matrix varies over time, the hedge ratio differs each period as well.

Kroner and Sultan (1993) combine the error correction model with the GARCH estimation. Specifically, they use the following model

$$\begin{bmatrix} \Delta S_t \\ \Delta F_t \end{bmatrix} = \begin{bmatrix} \mu_1 \\ \mu_2 \end{bmatrix} + \begin{bmatrix} \theta_s(S_{t-1} - F_{t-1}) \\ \theta_f(S_{t-1} - F_{t-1}) \end{bmatrix} + \begin{bmatrix} e_{1t} \\ e_{2t} \end{bmatrix}, \tag{4.28}$$

where S_t and F_t denotes logarithm prices, error process follows GARCH process and the hedge ratio is given by $H_{t-1} = \frac{G_{12,t}}{G_{22,t}}$, as before. However, they assume that the β parameter is equal to one. In other words, instead of regular stationary linear combination of spot and futures prices, they include the basis into the regression. Not only this is a generalization we want to avoid, but the basis can also be non-stationary, which would cause model misspecification. As we want the system of equations to be as well specified as possible, we conduct a univariate analysis at first to find out which variables best explain the changes in spot and futures prices separately. We include lags of the dependent variable and lags of the linear combination of the series as explanatory variables, and use the information criteria to choose the appropriate specification. Then we use the CCC-GARCH model to estimate the equations.

4.1.4 Akaike and Bayesian information criteria (AIC and BIC)

As we mention in the description of the individual econometric methods, the Akaike and Bayesian information criteria are used for evaluation of estimated models. Both criteria are based on likelihood function and they compare the positive effect of independent variables on the value of likelihood and their negative effect resulting from possible overfitting and loss of degrees of freedom.

The Akaike information criterion can be expressed as:

$$AIC = 2k - 2\ln(L), \tag{4.29}$$

where k stands for number of parameters in the model and L is maximized value of likelihood function for the model.

The value of the Bayesian criterion for large sample size, n, is:

$$BIC = -2\ln(L) + k\ln(n), \tag{4.30}$$

where k denotes number of parameters in the model and L is maximized value of likelihood function of the model, again.

The Bayesian information criterion has larger penalties for number of parameters in the model than the Akaike one. The “best” model is characterized by the minimum values of the information criteria.

4.2 Estimation of the Sharpe hedge ratio

The estimation of the Sharpe hedge ratio is based on Equation 3.12, where we replace the theoretical moments by the sample moments (e.g. the expected return can be replaced by the sample average return etc.) and simply calculate the hedge ratio. The Sharpe ratio approach includes a risk-free interest rate in the hedge ratio calculation. As the target of commodity hedging is to avoid losses caused by a decrease in the commodity price, we assume that the zero return is acceptable for a hedging company, so the risk-free return is set to 0.

Further, as pointed out by Chen et al. (2001), Sharpe ratio is non-linear function of hedge ratio, so finding the hedge ratio that maximizes Sharpe ratio is not straightforward. To be sure that we found the optimal hedge ratio we must either examine the second order conditions or plot a graph of Sharpe ratio on hedge ratio and find out whether we have the real maximum or a minimum of Sharpe ratio instead. We have decided to use the latter way for the examination.

Using the out-of-sample dataset, we compute hundreds of hedge ratios for slightly different samples, so we do not examine the graph for each optimal hedge ratio; we rather examine the graph of the first sample and then use the method of comparison of Sharpe ratios for the found hedge ratios. If there are insignificant differences among the optimal hedge ratios, we assume that the chosen hedge ratios are optimal without studying the graphs.

4.3 Estimation of the MEG hedge ratio

In our study, we restrict to the minimum MEG hedge ratio, whose estimation is based on Equation 3.14. Let us repeat it here:

$$\Gamma_v(R_p) = -vCov(R_p, (1 - G(R_p))^{v-1}). \tag{4.31}$$

The cumulative distribution function, G, is usually unknown, so we have to estimate it. Lerman and Yitzhaki (1984) suggest to use its empirical distribution; determination of the empirical distribution requires ranking the sample in the ascending order and dividing the rank by the size of the sample, $G(R_{p,i}) = \frac{Rank(R_{p,i})}{N}$. The sample points then stand for discrete estimates of G. For example, we have a sample $(R_{p,1}, R_{p,2}, R_{p,3}, R_{p,4})$ where $R_{p,2} > R_{p,4} > R_{p,1} > R_{p,3}$. Using the aforementioned approach, we get the following sample points of G: $\{2/4, 4/4, 1/4, 3/4\}$. Then we simply use the sample values to calculate the MEG coefficient, and the optimal hedge ratio is chosen to minimize the MEG coefficient. The simplest method to solve this problem is using a grid search, where we put thousands slightly different hedge ratios ($\Delta = 0.0001$) to the equation and then find the one minimizing the MEG coefficient.

It is also possible to use an approach proposed by Shalit (1995), who shows that the MEG hedge ratio can be expressed as:

$$H = \frac{Cov\{R_s, [1 - G(R_p)]^{v-1}\}}{Cov\{R_f, [1 - G(R_p)]^{v-1}\}}, \tag{4.32}$$

Lien and Shaffer (1999) note that if we add an assumption that the ranking of R_p, and R_f are identical, we can rewrite the hedge ratio as:

$$H = \frac{Cov\{R_s, [1 - \widehat{G(R_f)}]^{v-1}\}}{Cov\{R_f, [1 - \widehat{G(R_f)}]^{v-1}\}} = \frac{\sum_{t=1}^{T}(R_{s,t} - \bar{R}_s)(z_t - \bar{z})}{\sum_{t=1}^{T}(R_{f,t} - \bar{R}_f)(z_t - \bar{z})}, \tag{4.33}$$

where $z_t = [1 - \widehat{G(R_{f,t})}]^{v-1}$, $\bar{z}$, $\bar{R}_f$, $\bar{R}_s$ are means of z_t, $R_{f,t}$ and $R_{s,t}$, respectively, and $\widehat{G(R_f)}$ stays for empirical distribution of futures returns.

Lien and Shaffer further show that the assumption of identity of R_p and R_f ranking holds for hedge ratios smaller than one. This approach is very simple; to get the optimal hedge ratio, we only estimate the empirical distribution of futures returns and then plug the sample values into the equation.

The MEG hedge ratio operates with the risk parameter. We have decided to use the following five risk parameters in our study: 1.5, 2, 5, 10, and 20 to find out how the hedge ratio changes with increasing risk parameter.

We employ both types of the MEG hedge ratio calculation with all mentioned values of risk parameter and compare the results. We have to be aware that the approach suggested by Shalit is not appropriate in some cases as the assumption does not hold and the hedge ratio is larger than one. The Shalit's approach is marked as the MEG 1 or Gini 1 hedge ratio, and the method of grid search is marked as the MEG 2 or Gini 2 hedge ratio.

4.4 Estimation of the GSV hedge ratio

The GSV approach focuses only on returns lower than the target, which are undesirable in contrary to the above target returns. The GSV model can be rewritten to simplify the calculation as:

$$G_{\alpha,\delta}(R_p) = \frac{1}{T}\sum_{t=1}^{T}(\delta - R_{p,t})^{\alpha}U(\delta - R_{p,t}), \tag{4.34}$$

where

$$U(\delta - R_{p,t}) = \begin{cases} 1, & \text{for } \delta \geq R_{p,t} \\ 0, & \text{for } \delta < R_{p,t} \end{cases}$$

To find the optimal hedge ratio we use the same approach as in the first way of MEG hedge ratio estimation - the grid search. In this case, we save the GSV value for a slowly increasing series of hedge ratios and then identify the minimum value of GSV and pair it with the related hedge ratio. We should check whether the solution does not lie at a boundary of the hedge ratios interval; it would mean that the GSV value is decreasing with increasing/decreasing hedge ratio and the identified solution is not optimal.

When computing the GSV value, we have to define the target return. We suppose that a company hedges to prevent losses and 0% return would be acceptable, so we set the target equal to 0.

The GSV approach as well as the MEG coefficient uses the risk parameter; however, looking at the GSV hedge ratio for a chosen commodity, we find out that the GSV hedge ratio increases quicker with the increasing risk parameter than MEG hedge ratio and hence we choose smaller risk parameters, specifically 1, 2, 3, 4, and 5.

4.5 Estimation of the minimum VaR hedge ratio

The hedge ratio based on the minimum VaR is solved numerically. We must obtain the first derivative of the VaR with respect to the hedge ratio and set the result equal to zero to fulfil the first order condition. Recal the equation:

$$\frac{\partial \sigma_p}{\partial H}(A_1 + A_2 s_p + A_3 k_p 1 A_4 s_p^2) + \sigma_p(A_2\frac{\partial s_p}{\partial H} + A_3\frac{\partial k_p}{\partial H} + 2A_4 s_p\frac{\partial s_p}{\partial H}) = 0,$$

where $A_1 = c(\alpha) - \frac{1}{8}[c(\alpha)^3 - 3c(\alpha)]$, $A_2 = \frac{1}{6}[c(\alpha)^2 - 1]$, $A_3 = \frac{1}{24}[c(\alpha)^3 - 3c(\alpha)]$, and $A_4 = \frac{1}{36}[2c(\alpha)^3 - 5c(\alpha)]$.

The skewness and kurtosis functions used for calculation of VaR are complex and contain hedge ratios of high powers leading to non-linearity of VaR in the hedge ratio. We face a similar problem as in the case of Sharpe ratio; we often obtain more values of hedge ratio fulfilling the first order condition and it is necessary to verify the second order condition or to examine the graph of the VaR on hedge ratio.

As we mostly obtain more values of hedge ratio satisfying the first order condition, we first compute the value of VaR for each hedge ratio to identify the one which is most probably the optimal one, and then we verify its optimality using the graphs. In the out-of-sample part of data, we use the same approach as in the case of Sharpe ratio.

We use 95% VaR, so we have $c(0.05) = -1.645$.

4.6 Efficiency analysis

To compare and evaluate the results, we divide the dataset to the in-sample part used for estimation and the out-of-sample part used for evaluation of the results. A reduction in returns variance and VaR are used for measurement of the results and comparison of individual hedging ratios. We define the reduction in the returns variance as:

$$e = 1 - \frac{var(R_p)}{var(R_s)}. \tag{4.35}$$

The Value at Risk is computed using the Cornish-Fisher expansion that we use for finding the minimum VaR hedge ratio. It is defined as:

$$\begin{aligned} VaR_p = -\sigma_p c(\alpha) + \frac{1}{6}[c(\alpha)^2 - 1]s_p + \frac{1}{24}[c(\alpha)^3 - 3c(\alpha)](k_p - 3) - \\ -\frac{1}{36}[2c(\alpha)^3 - 5c(\alpha)]s_p^2, \end{aligned} \tag{4.36}$$

where $c(\alpha)$ stands for the α percent quantile of the standard normal distribution and it is a negative number. As mentioned above, we calculate 95% VaR which corresponds to $c(0.05) = -1.645$.

We evaluate the performance of hedge ratios in the in-sample part as well, even though it does not correspond to hedging in the real world, where the historical data are used for estimation of hedge ratio for the future period. We use the estimated hedge ratios and apply the hedging strategy on daily data. Except for the bivariate GARCH models, all hedge ratios are constant. For the bivariate GARCH models we evaluate both, hedging with changing hedge ratios and hedging with average hedge ratios. We calculate reduction in returns variance and VaR and compare the results.

There are several approaches how to compare the power of individual hedge ratios using the out-of-sample data. We can simple use the estimated hedge ratios from the in-sample part of data and apply them on the out-of sample data. However, this would be unrealistic as the hedging period would be too long and the company would not change the hedge ratio over the period (except for the hedge ratio given by the bivariate GARCH, again). Or we may use a more realistic approach and re-estimate the hedge ratio periodically using the estimate as hedge ratio for the next period.

As the hedging period should be the same as the frequency of the data and our data sample is limited, we have decided to use the daily hedging period to ensure reliability of the analysis, but we are aware of the fact that most of companies using hedging do not adjust their hedge ratio daily because it would be too expensive due to transaction costs.

We use the rolling window method with 1000 last historical observations at t used to estimate the hedge ratio employed at $t+1$, in $t+1$ we roll over the sample and use 1000 last observations to estimate the hedge ratio for $t+2$, and so on. It is not a strictly out-of-sample approach, but we think it is the most realistic one and it is suitable to be applied on our data.

In the last part of the efficiency analysis, we try to employ the daily data, yet we extend the hedging period. It is assumed, that the hedge period is one week (5 working days), meaning that the company adjusts the hedge ratio weekly. The hedge ratios are estimated on daily basis and the company calculates the average hedge ratio from the past week data and uses it as the hedge ratio for the following week. Again, we compare the power of the hedge ratios using the reduction in variance and VaR.

4.7 Programs used in the analysis

For estimation of the optimal hedge ratios we use two different programs – STATA and Matlab. STATA is used for the econometric analysis of the minimum variance hedge ratio and Matlab is used for numerical derivation of the hedge ratios in case of minimum VaR hedge ratio, Sharpe hedge ratio, minimum MEG hedge ratio, and minimum GSV hedge ratio. These hedge ratios are found either using the first order conditions or grid search. The programs written to find the optimal hedge rations in Matlab can be found in the Appendix.

We must also use programming in STATA, as the incorporated rolling window options are limited and do not enable us to use multiple steps process necessary in case of the error correction models and the multivariate GARCH models. As we use the rolling window approach to find the hedge ratios in the out-of-sample data amounting to hundreds of observations, we use for cycles in the *do.* file in STATA to estimate them. These codes are enclosed in the Appendix as well.

Chapter 5

Empirical analysis

In this chapter, we describe the data used in our analysis and evaluate the results of the procedures described in the previous section.

5.1 Data description

Each futures contract is usually active (regarding trading) only in the last three months, when it is the futures with maturity closest to the current date. Further, prices during the delivery month are volatile and unreliable. Therefore, we have decided to use nearby futures contracts and replace the current nearby contract by the following nearby contract on the first day of the settlement month in order to provide reliable data. Nearby futures contract is a contract with the nearest delivery month to the trading day.[3] Nearby futures are linked to create a continuous series of futures prices. When calculating the daily returns, we ensure that the differences are made using prices of one contract, which is especially important at the point of rolling futures over; mixing prices of two different futures together would distort the results and the returns would not correspond to the market behaviour.

To create such a series, we need separate data about each futures contract with settlement day in a chosen historical period. We tried to find the data using the Reuters Eikon tool; however, the historical data are presented as continuous contracts there and we did not find any detailed description of their composition. As we strictly need to generate the specific series described above,

[3]For example, let us have two futures contracts on Wheat, one with settlement day on May 15, 2014 and the other with settlement day on July 15, 2014. On April 20, 2014, the nearby futures is the first one, but as we reach May 1, 2014 the nearby futures changes to the second one with settlement day in July.

we have to rely on the only free database providing the daily data about spot and futures prices of commodities: www.quandl.com.

The spot prices presented in the database are obtained from the Wall Street Journal Market Data Center (WSJ MDC), which publishes daily spot prices since May 1, 2007; further, it contains an outage in published data in fall 2013 and thus limits our dataset from both sides to a period ranging from May 1, 2007 to August 31, 2013. Most of the used futures are traded on the Chicago Mercantile Exchange (CME), the Chicago Board of Trade (CBOT) and the New York Mercantile Exchange (NYMEX). In this selection, we try to cover all types of commodities. A detailed overview of used commodities and related data can be found in Table 5.1.

Table 5.1: Commodities overview

Commodity	**Type**	**Spot**	**Source**
Beef	Farms and fishery	Beef, Select, gr. 1-3	USDA via WSJ
Coffee	Agriculture, softs	Coffee, Colombian, NY	WSJ
Copper	Industrial metals	Copper, gr. high	Comex via WSJ
Corn	Agriculture, grains	#2 Yellow C., Central Illinois	USDA via WSJ
Oil	Energy	WTI Crude Oil	US Dep. of Energy
Platinum	Rare metals	Platinum, Engelhard fabr. p.	WSJ
Soybeans	Agriculture, grains	#1 Yellow S., Illinois	USDA via WSJ
Wheat	Agriculture, grains	#2 Soft Red W., St Louis	USDA via WSJ

Futures	**Settlement months**	**Exchange**	**Cont. un.**
45% Select, gr. 3, live	Feb,Apr,Jun,Aug,Oct,Dec	CME	40,000 p.
Arabica Coffee ("C")	Mar,May,Jul,Sep,Dec	ICE	37,500 p.
Copper, gr. 1 El. Cathodes	Mar,May,Jul,Sep,Dec	COMEX	25,000 p.
#2 Yellow C.	Mar,May,Jul,Sep,Dec	CBOT	5,000 b.
Light Sweet Crude Oil	Jan-Dec,monthly	NYMEX	1,000 br.
Platinum, min 99.95% pure	Jan,Apr,Jul,Oct	NYMEX	50 t.o.
#1 Yellow S., 6% premium	Jan,Mar,May,Jul,Aug,Sep,Nov	CBOT	5,000 b.
#2 Soft Red Winter W.	Mar,May,Jul,Sep,Dec	CME	5,000 b.

Note: p.=pounds, b.=bushels, t.o.=troy ounces, br.=barrels

We did not find corresponding spot prices for some commodity futures; hence, the closest substitutes are used instead. For example, there are futures for Live Cattle, but the spot prices reported by the WSJ MDC contain only spot prices for Beef; similarly, the main underlying asset for Soybeans futures are #2 Yellow Soybeans and we have data about #1 Yellow Soybeans, which can be traded under the Soybeans futures as well but with a 6% premium. These discrepancies may cause weaker correlation between the spot and futures prices and price returns. Nevertheless, this is a real problem faced by hedging companies; a specific asset they want to hedge is hardly ever covered by futures, so they have to use a similar asset with correlated prices and price returns.

Daily data from period May 1, 2007 - August 31, 2013 are collected, amounting to approximately 1600 observations. We divide the data sample into two sub-samples, one is used for the in-sample analysis and the other is used for evaluation of the results. The analysis is performed using the first 1000 observations (approximately two thirds); the remaining observations (one third) are then used for evaluation of the hedge efficiency.

We use price logarithms and their differences as it is the standard approach to deal with daily financial data. Note that differences of logarithms can be considered returns. Overview of statistic properties of the data can be found in Table 5.2.

Table 5.2: Statistics of spot and futures returns

Com.		# obs.	mean	min	max	SD	skewn.	kurt.
Beef	spot	1597	0.00013	-0.02545	-0.03444	0.00574	0.66850	6.88984
	fut.	1597	-0.00027	0.03685	0.03576	0.00863	-0.12892	4.29509
Coffee	spot	1596	0.00013	-0.09529	0.07151	0.01452	-0.33878	5.64634
	fut.	1596	-0.00017	-0.11254	0.07510	0.01891	-0.24657	4.57074
Copper	spot	1597	-0.00005	-0.11693	0.11769	0.02134	-0.11060	5.73470
	fut.	1597	-0.00011	-0.11506	0.08677	0.02108	-0.13169	5.32469
Corn	spot	1595	0.00011	-0.12112	0.10888	0.02330	-0.21902	5.26587
	fut.	1595	0.00000	-0.10409	0.08662	0.02145	-0.14973	4.50513
Oil	spot	1599	0.00029	-0.12827	0.16414	0.02520	0.09122	8.56198
	fut.	1599	-0.00013	-0.11433	0.13340	0.02309	-0.22963	6.60682
Platinum	spot	1614	0.00005	-0.10048	0.10981	0.01574	-0.65839	8.60172
	fut.	1614	-0.00001	-0.11147	0.08138	0.01681	-0.67533	7.54907
Soybeans	spot	1599	0.00036	-0.12737	-0.07411	0.01853	-0.59680	6.20499
	fut.	1599	0.00068	0.07345	0.06476	0.01729	-0.31581	4.71835
Wheat	spot	1599	0.00019	-0.21770	0.18684	0.03163	-0.26102	7.37045
	fut.	1599	-0.00040	-0.10017	0.08794	0.02387	-0.08397	4.29273

All means of price returns are very close to zero, which supports the usage of our zero means assumption in the minimal Value at Risk hedge ratio. Every mean of spot returns except for the return on spot Corn is positive, whereas the futures returns are mostly negative. The lower mean returns on futures are balanced by lower standard deviations in the returns for all Grains, Oil and Copper. The biggest difference between the spot and futures returns' standard deviations can be observed on the example of Wheat: the standard deviation of futures returns equals to 2/3 of the standard deviation of spot returns. If the spot and futures returns are highly correlated, it is possible that the hedge ratio is higher than one to cover the changes in spot returns by smaller changes in futures returns.

Skewness of a symmetric distribution is equal to 0; all returns except for spot returns on Oil and Beef have negative skewness meaning that their distributions have long left tails. In other words, small gains are quite frequent but there are a few extreme losses as well (considering zero mean). Kurtosis of all returns is higher than kurtosis of normal distribution, meaning that their distributions are leptokurtic or sharper than the normal distribution and have fat tails. Fat tails signal a higher probability of extreme values.

The skewness and kurtosis results show that the returns series are not normally distributed, and support the approach used by Cao et al. (2010), who deals with non-normally distributed series in the calculation of the Value at Risk hedge ratio. The largest departure from normality is for Platinum spot and futures returns, which have skewness coefficients equal to -0.668 and -0.675, respectively, and their kurtosis coefficients take value of 8.60 for spot returns and 7.55 for futures returns. The graphs of returns are presented in Figure B.1 in the Appendix and show that the returns oscillate around zero. In the graph of Wheat spot and futures prices, it is visible that the spot return volatility is much higher than the futures return volatility. The higher volatility in the first third of the series of Beef, Copper, Corn, Oil, Platinum, and Soybeans is associated with the financial crisis.

An important factor influencing hedge ratio is the correlation between the spot and futures returns. As we choose individual commodities, we try to obtain spot and futures prices of the closest assets based on the description and trends in prices, but this approach does not ensure correlation of the returns as presented in Table 5.3.

Table 5.3: Correlation of spot and futures returns

Correlation	levels	differences
Beef	0.9383	0.0681
Coffee	0.8957	-0.0156
Copper	0.9997	0.9570
Corn	0.9850	0.8655
Oil	0.9971	0.9258
Platinum	0.9988	0.7335
Soybeans	0.9908	0.9289
Wheat	0.8899	0.8214

Spot and futures returns on Beef are correlated only very weakly with correlation coefficient equal to 0.068. The returns on Coffee spot and futures are actually negatively correlated, even though the correlation of levels and graphs of levels indicate that the assets given by spot and futures are a good match. (The graphs are presented in Figure B.2 in the Appendix.) Although the futures are clearly a bad hedging tool for the commodities and a hedging company would not choose them to hedge its position, we do not exclude them from the hedging ratio analysis to examine the effect of poorly chosen futures on hedging.

Other commodities are highly correlated in both, levels and returns, and hence the futures for hedging are well chosen. We can now move to the hedge ratio estimations.

5.2 Results

The approaches to the hedge ratio estimation can be divided into two groups - one is based on econometric analysis and the other employs numerical-solving methods. As the econometric part is more complex we describe the results of individual parts of the whole process in a separate subsection.[4]

The numerical-solving based methods of finding hedge ratios are thoroughly described in the previous chapter and we do not repeat them here, only a discussion of results is provided in this section. For more details, return to the previous chapter or see the Matlab code presented in the Appendix.

5.2.1 Econometric Analysis

We start the econometric analysis with the unit root test to determine whether the levels or the differences are stationary. Based on the graphs of returns, we employ Augmented Dickey Fuller test without constant. The regressions with different number of lags (0-5) are estimated and we keep the results of the one with significant coefficients only. We are not able to reject the null hypothesis of unit root for the levels of spot and futures prices of all commodities at a 10% level of significance and we conclude that the price levels are not stationary. The test is then applied to returns; in this case, we reject the null hypothesis of unit root for all returns. The conclusion of unit root analysis is the finding that all spot and futures price series are integrated of order one, so we have to

[4] All presented results are for the first 1000 observations.

use its differences in the econometric analysis. The results of tests are shown in Table 5.4.

Table 5.4: Results of unit root test

		levels				differencies			
Com.	returns	const.	# lags	t. stat.	p-value	const.	# lags	t. stat.	p-value
Beef	spot	no	4	0.491	>10%	no	0	-9.628	<1%
	futures	no	0	0.636	>10%	no	0	-31.101	<1%
Coffee	spot	no	0	2.005	>10%	no	2	-16.455	<1%
	futures	no	0	1.523	>10%	no	0	-32.749	<1%
Copper	spot	no	4	-0.122	>10%	no	3	-15.085	<1%
	futures	no	1	-0.041	>10%	no	3	-15.14	<1%
Corn	spot	no	0	0.721	>10%	no	0	-31.394	<1%
	futures	no	0	0.764	>10%	no	0	-30.337	<1%
Oil	spot	no	3	0.464	>10%	no	4	-14.774	<1%
	futures	no	0	0.529	>10%	no	0	-32.664	<1%
Plat.	spot	no	0	0.481	>10%	no	0	-31.054	<1%
	futures	no	1	0.432	>10%	no	0	-29.636	<1%
Soyb.	spot	no	0	0.775	>10%	no	0	-31.626	<1%
	futures	no	0	0.74	>10%	no	0	-30.722	<1%
Wheat	spot	no	1	0.176	>10%	no	0	-34.861	<1%
	futures	no	0	0.246	>10%	no	0	-32.181	<1%

1% critical value = -2.58, 5% critical value = -1.95, 10% critical value = -1.62

Then we run the simple OLS regression to obtain the basic hedge value determined by the coefficient β_0 in the regression model

$$\Delta S_t = \alpha + \beta_0 \Delta F_t + \epsilon_t.$$

The results for each commodity are presented in Table 5.5.

All β_0 coefficients except for Coffee are significant. Albeit insignificant, β_0 for Coffee is negative, reflecting the negative correlation between the spot and futures returns. The coefficient for Beef is significant but low, signalling that the ratio between number of futures used for hedging and the related spot position is very small. The Coffee and Beef models have low Adjusted R^2 arising from the very weak correlation, we would thus mark both of the models as poor and unreliable.

The values of Adjusted R^2 of other models are much higher, taking values in range between 0.54 and 0.92 (for Platinum and Copper, respectively). There is a clear positive relationship between the quality of model measured by Adjusted R^2 and the correlation between spot and futures returns. β_0 coefficient in the Platinum model is the smallest one taking value of 0.7, the other are much closer to 1, and the coefficients for Oil and Wheat are even larger than one,

Table 5.5: Results of simple OLS regression

	Beef	Coffee	Copper	Corn	Oil	Plat.	Soyb.	Wheat
β_0	0.0431*	-0.0032	0.9701*	0.9691*	1.0150*	0.6976*	0.9910*	1.1601*
	(0.021)	(0.024)	(0.009)	(0.018)	(0.015)	(0.021)	(0.012)	(0.024)
α	0.0002	0.0010*	0.0001	0.0006	0.0006	0.0001	-0.0002	0.0007
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Adj. R^2	0.0034	0.0010	0.9187	0.7550	0.8284	0.5340	0.8726	0.7018
S. corr.[1]	0	0.5420	0	0	0.3995	0	0	0
Heter.[2]	0.5304	0.6821	0	0.7671	0	0.0103	0	0.0037
ARCH[3]	0.0579	0.0001	0	0	0	0	0	0
AIC	-7422	-5664	-7123	-5906	-5995	-5976	-6995	-5035
BIC	-7412	-5654	-7113	-5896	-5985	-5966	-6985	-5025

[1]p-value, Breusch-Godfrey LM test for autocorrelation, 2 lags, H0: no autocorrelation
[2]p-value, Breusch-Pagan test for heteroskedasticity, H0: no heteriskedasticity
[3]p-value, LM test for autoregressive cond. heteroskedasticity, 1 lag, H0: no ARCH eff.
*significant at 5% level

Table 5.6: Results of specified OLS regression

	Beef	Coffee	Copper	Corn	Oil	Plat.	Soyb.	Wheat
β_0	0.0544*	0.0246	0.9738*	0.9728*	simple	0.6747*	0.9951*	1.1621*
	(0.018)	(0.013)	(0.009)	(0.016)	OLS	(0.017)	(0.012)	(0.024)
γ_1	0.4177*	-0.2458*	-0.3611*	-0.4007*	best	-0.4327*	-0.2591*	-0.1467*
	(0.028)	(0.030)	(0.029)	(0.029)		(0.026)	(0.031)	(0.031)
β_1	0.1025*	0.6039*	0.3601*	0.4648*		0.5586*	0.2504*	0.0806
	(0.018)	(0.013)	(0.030)	(0.032)		(0.025)	(0.033)	(0.043)
β_2	-	0.2514*	0.0235*	-		-	-	-
		(0.022)	(0.009)					
α	0.0002	0.0006*	0.0001	0.0008*		0.0001	-0.0002	0.0008
	(0.000)	(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.001)
Adj. R^2	0.2097	0.6788	0.9299	0.7986		0.6925	0.8809	0.7119
S. corr.[1]	0	0.0036	0	0		0	0.1449	0.9378
Heter.[2]	0.0001	0.0003	0	0.0219		0.5948	0.9272	0.6744
ARCH[3]	0.0058	0	0	0		0	0	0
AIC	-7644	-6781	-7254	-6093		-6382	-7052	-5062
BIC	-7624	-6756	-7229	-6074		-6362	-7033	-5042

[1]p-value, Breusch-Godfrey LM test for autocorrelation, 2 lags, H0: no autocorrelation
[2]p-value, Breusch-Pagan test for heteroskedasticity, H0: no heteriskedasticity
[3]p-value, LM test for autoregressive cond. heteroskedasticity, 1 lag, H0: no ARCH eff.
*significant at 5% level

meaning that a hedging company has to use more units of underlying asset at futures market than it owns at spot market to hedge its position.

Most of the models have autocorrelated or heteroskedastic errors and show signs of ARCH effect; hence, we try to specify the models better.

The specification can be improved using lag values of both dependent and independent variables. The best model is determined by information criteria. The general model can be written as:

$$\Delta S_t = \alpha + \beta_0 \Delta F_t + \gamma_1 \Delta S_{t-1} + \beta_1 \Delta F_{t-1} + \beta_2 \Delta F_{t-2} + \gamma_2 \Delta S_{t-2} + \epsilon_t,$$

but some of the coefficients can be zero to specify the desired model. The results are presented in Table 5.6.

Several combinations of lags are tried for each model and the best specified models are chosen according to the information criteria. The best model of Oil has no lags; one lag of the dependent and independent variables is added to the other models, and Coffee and Copper models contain two lags of the independent variable. The improvement can be tracked using the values of information criteria and Adjusted R^2. The biggest improvement in terms of Adjusted R^2 can be observed in Beef and Coffee models. The β_0 coefficient increases in most of the models, but the difference between the two coefficients is insignificant for models with good explanatory power.

The residuals of the five models are still autocorrelated, so the specification of the models is not ideal despite the improvements.

As all our series are integrated of order one, it is appropriate to test the presence of cointegration. Results can be found in Table 5.7.

Table 5.7: Results of cointegration test

Com.	const.	# lags	t. stat.	p-value	coeff.
Beef	no	1	-3.811	<1%	1.0778
Coffee	no	3	-0.646	>10%	-
Copper	no	4	-7.153	<1%	1.0002
Corn	no	2	-3.315	<1%	0.9570
Oil	no	2	-8.123	<1%	0.9976
Platinum	no	4	-3.495	<1%	1.0092
Soybeans	no	2	-4.232	<1%	0.9895
Wheat	no	1	-1.763	5%>x<10%	0.9101

All series except for Coffee have cointegrated spot and futures returns, so we improve the OLS models by including the error term:

$$\Delta S_t = \alpha + \beta_0 \Delta F_t + \delta_1 z_{t-1} + \epsilon_t$$

and

$$\Delta S_t = \alpha + \beta_0 \Delta F_t + \gamma_1 \Delta S_{t-1} + \beta_1 \Delta F_{t-1} + \gamma_2 \Delta S_{t-2} + \beta_2 \Delta F_{t-2} + \delta_1 z_{t-1} + \epsilon_t,$$

where z_{t-1} is lag of the linear combination of spot and futures prices. The results are shown in Tables 5.8 and 5.9

Table 5.8: Results of simple ECM regression

	Beef	Coffee	Copper	Corn	Oil	Plat.	Soyb.	Wheat
β_0	0.0475*	not	0.9746*	0.9703*	1.0275*	0.6989*	0.9901*	1.1636*
	(0.020)	cointegr.	(0.008)	(0.017)	(0.014)	(0.019)	(0.012)	(0.024)
δ_1	-0.0239*		-0.3889*	-0.0887*	-0.1022*	-0.2384*	-0.0623*	-0.0113*
	(0.003)		(0.025)	(0.013)	(0.013)	(0.018)	(0.008)	(0.004)
α	0.0003		-0.0002	0.0003	0.0005	0.0003	-0.0002	0.0006
	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Adj. R^2	0.0531		0.9347	0.7658	0.8378	0.601	0.8799	0.7037
S. corr.[1]	0.0042		0.0001	0.0392	0.0448	0.0012	0.0128	0.0212
Heter.[2]	0.2999		0.0945	0.0392	0	0.0002	0	0.0044
ARCH[3]	0.0158		0	0	0	0	0	0
AIC	-7472		-7340	-5950	-6051	-6130	-7053	-5041
BIC	-7457		-7325	-5936	-6036	-6115	-7038	-5026

[1]p-value, Breusch-Godfrey LM test for autocorrelation, 2 lags, H0: no autocorrelation
[2]p-value, Breusch-Pagan test for heteroskedasticity, H0: no heteriskedasticity
[3]p-value, LM test for autoregressive cond. heteroskedasticity, 1 lag, H0: no ARCH eff.
[*]significant at 5% level

The error correction term is significant in all models; the values of Adjusted R^2 increase, and the information criteria suggest that the models with the error correction term are better than the simple models. The estimators of hedge ratio increase compared to the simple models and the problem of autocorrelation and heteroskedasticity in residuals diminishes.

According to the ARCH test, the ARCH effect is present in the models of all commodities, so we use the GARCH (1,1) suggested by the authors discussed in Chapter 3. Again, two models are used - a simple one

$$\Delta S_t = \alpha + \beta_0 \Delta F_t + \epsilon_t$$
$$\sigma_t^2 = \lambda_0 + \lambda_1 \sigma_{t-1}^2 + \theta_1 \epsilon_{t-1}^2,$$

Table 5.9: Results of specified ECM regression

	Beef	Coffee	Copper	Corn	Oil	Plat.	Soyb.	Wheat
β_0	0.0596*	not	0.9774*	0.9731*	simple	0.6827*	0.9941*	1.1632*
	(0.018)	cointegr.	(0.008)	(0.016)	ECM	(0.016)	(0.011)	(0.024)
γ_1	0.3387*		-0.3235*	-0.3723*	best	-0.5654*	-0.2560*	-0.0941*
	(0.031)		(0.034)	(0.029)		(0.032)	(0.030)	(0.017)
β_1	0.0955*		0.3215*	0.4389*		0.6141*	0.2472*	-
	(0.018)		(0.034)	(0.032)		(0.028)	(0.032)	
γ_2	0.1129*		-0.2252*	-		-0.1919*	-	-
	(0.031)		(0.030)			(0.028)		
β_2	0.0482*		0.2397*	-		0.2705*	-	-
	(0.018)		(0.031)			(0.029)		
δ_1	-0.0153*		-0.2416*	-0.0584*		-0.0817*	-0.0616*	-0.0091*
	(0.003)		(0.028)	(0.012)		(0.017)	(0.008)	(0.004)
α	0.0002		-0.0001	0.0006		0.0002	-0.0002	0.0006
	(0.000)		(0.000)	(0.000)		(0.000)	(0.000)	(0.001)
Adj. R^2	0.2460		0.9411	0.8030		0.7289	0.8881	0.7123
S. corr.[1]	0.0231		0.9884	0.0523		0.0389	0.0053	0.0574
Heter.[2]	0.0002		0.8810	0.5515		0.0021	0.0155	0.3654
ARCH[3]	0.016		0	0		0	0	0
AIC	-7679		-7426	-6114		-6497	-7113	-5063
BIC	-7645		-7392	-6090		-6463	-7089	-5043

[1]p-value, Breusch-Godfrey LM test for autocorrelation, 2 lags, H0: no autocorrelation
[2]p-value, Breusch-Pagan test for heteroskedasticity, H0: no heteriskedasticity
[3]p-value, LM test for autoregressive cond. heteroskedasticity, 1 lag, H0: no ARCH eff.
[*]significant at 5% level

and the model with the best information criteria

$$\Delta S_t = \alpha + \beta_0 \Delta F_t + \gamma_1 \Delta S_{t-1} + \beta_1 \Delta F_{t-1} + \gamma_2 \Delta S_{t-2} + \beta_2 \Delta F_{t-2} + \delta_1 z_{t-1} + \epsilon_t$$
$$\sigma_t^2 = \lambda_0 + \lambda_1 \sigma_{t-1}^2 + \theta_1 \epsilon_{t-1}^2.$$

Some of the β_i and γ_i coefficients can be again equal to zero. The results are in Tables 5.10 and 5.11.

Table 5.10: Results of simple GARCH(1, 1) regression

	Beef	Coffee	Copper	Corn	Oil	Plat.	Soyb.	Wheat
β_0	0.0398*	-0.0584*	not	1.0857*	1.0028*	0.6904*	1.0072*	1.2042*
	(0.019)	(0.015)	converge	(0.004)	(0.003)	(0.017)	(0.008)	(0.014)
α	0.0002	0.0016*		0.0011*	0.0002*	0.0001	0.0002	-0.0002
	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
θ_1	0.1391*	0.2307*		1.0741*	0.7107*	0.1168*	0.4408*	0.7472*
	(0.036)	(0.031)		(0.073)	(0.022)	(0.015)	(0.041)	(0.075)
λ_1	-0.1607	0.3617*		0.5178*	0.5954*	0.8834*	0.5629*	0.0463
	(0.090)	(0.066)		(0.012)	(0.006)	(0.011)	(0.023)	(0.024)
λ_0	0.0000*	0.0001*		0.0000*	0.0000*	0.0000*	0.0000*	0.0002*
	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log likel.	3721	2868		3467	3966	3176	17904	2634
AIC	-7433	-5725		-6925	-7922	-6342	-7681	-5258
BIC	-7408	-5701		-6900	-7897	-6317	-7656	-5234

*significant at 5% level

The GARCH estimation is based on the maximum likelihood method, which is an iterative procedure converging when the difference between two iterations is small enough. We encounter the problem of non-converging likelihood several times in our study. GARCH model likelihoods are notoriously difficult to maximize and solving the problem is beyond the scope of the thesis;[5] hence, the GARCH results are not presented for Copper and the hedge ratio estimated using the specified GARCH model was not found either for Beef and Wheat.

The Beef time series data do not strictly reject the null hypothesis of no ARCH effect and the GARCH model has a zero impact on the information criteria. The information criteria of the other models, on the contrary, significantly increase. The reaction of the hedge ratios on the change in the type of estimation differs across the commodities. As STATA do not report Ad-

[5] Further, we want stay consistent in estimations of the hedge ratios for different commodities, so we do not use any specification of GARCH options or different methods of estimation. Another problem with the GARCH estimation is that the non-convergence issue often appears somewhere in the out-of-sample data that are used for the rolling window procedure, e.g. the estimation is run 600 times and finding an option convenient for all regression would be very time demanding.

Table 5.11: Results of specified GARCH(1, 1) regression

	Beef	Coffee	Copper	Corn	Oil	Plat.	Soyb.	Wheat
β_0	not	0.0326*	not	1.0830*	1.0039*	0.6647*	0.9933*	not
	converge	(0.009)	converge	(0.006)	(0.003)	(0.013)	(0.003)	converge
γ_1		-0.1150*		-0.2665*	-	-0.5478*	-0.1499*	
		(0.037)		(0.042)		(0.033)	(0.041)	
β_1		0.6185*		0.2732*	-	0.5913*	0.1441*	
		(0.009)		(0.045)		(0.027)	(0.041)	
γ_2		-		-	-	-0.1903*	0.0100	-
						(0.028)	(0.029)	
β_2		0.1677*		-	-	0.2606*	-0.0533	
		(0.024)				(0.030)	(0.029)	
δ_1		-		-0.0168*	-0.1342*	-0.0916*	-0.0139*	
				(0.003)	(0.007)	(0.017)	(0.003)	
α		0.0006*		0.0014*	0.0012*	-0.0002	0.0010*	
		(0.000)		(0.000)	(0.000)	(0.000)	(0.000)	
θ_1		0.4137*		1.0787*	0.8109*	0.0865*	1.6838*	
		(0.040)		(0.078)	(0.028)	(0.013)	(0.162)	
λ_1		0.1054*		0.5226*	0.4969*	0.9111*	0.3768*	
		(0.049)		(0.016)	(0.013)	(0.011)	(0.020)	
λ_0		0.0000*		0.0000*	0.0000*	0.0000*	0.0000*	
		(0.000)		(0.000)	(0.000)	(0.000)	(0.000)	
Log likel.		3481		3482	4021	3431	3910	
AIC		-6947		-6948	-8029	-6841	-7800	
BIC		-6907		-6909	-8000	-6792	-7751	

*significant at 5% level

justed R^2 for GARCH estimations, we express the fitting quality using the log likelihood values, which cannot be compared to the previous estimations. More details regarding the hedge ratio estimation can be found in the following subsection comparing the results.

The last model we employ is the bivariate GARCH model - again in the basic and specified versions. The specification for each variable is determined using the univariate analysis and information criteria. While in the other models the hedge ratio was given by the estimated β_0 coefficient, it is determined by the variance-covariance matrix in the bivariate GARCH model. The models are

$$\begin{aligned}
\Delta S_t &= \alpha_1 + \epsilon_{1,t} \\
\sigma^2_{1,t} &= \lambda_{10} + \lambda_{11}\sigma^2_{1,t-1} + \theta_{11}\epsilon^2_{1,t-1} \\
\Delta F_t &= \alpha_2 + \epsilon_{2,t} \\
\sigma^2_{2,t} &= \lambda_{20} + \lambda_{21}\sigma^2_{2,t-1} + \theta_{21}\epsilon^2_{2,t-1}
\end{aligned}$$

and

$$\begin{aligned}
\Delta S_t &= \alpha_1 + \gamma_{11}\Delta S_{t-1} + \delta_{11}z_{t-1} + \epsilon_{1t} \\
\sigma^2_{1,t} &= \lambda_{10} + \lambda_{11}\sigma^2_{1,t-1} + \theta_{11}\epsilon^2_{1,t-1} \\
\Delta F_t &= \alpha_2 + \beta_{21}\Delta S_{t-1} + \delta_{21}z_{t-1} + \epsilon_{2,t} \\
\sigma^2_{2,t} &= \lambda_{20} + \lambda_{21}\sigma^2_{2,t-1} + \theta_{21}\epsilon^2_{2,t-1}
\end{aligned}$$

The hedge ratio is then defined as $H_{t-1} = \frac{G_{12,t}}{G_{22,t}}$, where $G_{12,t}$ and $G_{22,t}$ are elements of the variance-covariance matrix. Results can be found in Tables 5.12 and 5.13.

We cannot make any conclusions about the hedge ratio based on the regression results as it is given by estimation of the variance-covariance matrix and varies over time. The estimations of the bivariate GARCH models have the highest information criteria, so we can conclude that the models fit the data best and we suppose that the related hedge ratios are the most efficient out of the econometric hedge ratios. We examine this hypothesis in the following section.

Table 5.12: Results of simple bivariate GARCH regression

	Beef	Coffee	Copper	Corn	Oil	Plat.	Soyb.	Wheat
α_1	0.0001	0.0015*	0.0010	0.0033*	0.0026*	0.0006	0.0011	0.0015
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)
θ_{11}	0.1543*	0.1999*	0.0738*	0.1659*	0.1188*	0.0693*	0.0438*	0.0921*
	(0.047)	(0.049)	(0.007)	(0.029)	(0.011)	(0.011)	(0.005)	(0.015)
λ_{11}	-0.1448*	0.4472*	0.9471*	0.7651*	0.9026*	0.9262*	0.9472*	0.8935*
	(0.063)	(0.149)	(0.005)	(0.042)	(0.008)	(0.011)	(0.007)	(0.018)
λ_{10}	0.0000*	0.0001*	0.0000*	0.0001*	0.0000	0.0000*	0.0000*	0.0000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
α_2	-0.0002	0.0007	0.0009	0.0026*	0.0021*	0.0006	0.0013*	0.0005
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)
θ_{21}	0.0342*	0.0219*	0.0755*	0.1573*	0.1040*	0.0652*	0.0377*	0.0572*
	(0.009)	(0.010)	(0.007)	(0.027)	(0.011)	(0.011)	(0.005)	(0.012)
λ_{21}	0.9515*	0.9417*	0.9464*	0.7756*	0.9166*	0.9196*	0.9524*	0.9013*
	(0.013)	(0.024)	(0.005)	(0.042)	(0.008)	(0.014)	(0.007)	(0.023)
λ_{20}	0.0000	0.0000	0.0000*	0.0000*	0.0000*	0.0000*	0.0000*	0.0000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log likel.	7043	5406	6116	5412	5976	5889	6128	4907
AIC	-14067	-10794	-12214	-10807	-11934	-11760	-12238	-9797
BIC	-14023	-10750	-12170	-10762	-11890	-11715	-12194	-9752

*significant at 5% level

Table 5.13: Results of specified bivariate GARCH regression

	Beef	Coffee	Copper	Corn	Oil	Plat.	Soyb.	Wheat
γ_{11}	0.4418*	not	-	-	-	-	-	not
	(0.031)	converge						converge
$\delta_1 1$	-0.0183*		-3.3303*	0.0791*	-	-0.2956*	-	
	(0.003)		(0.165)	(0.025)		(0.020)		
α_1	0.0001		-0.0033*	0.0023*	0.0028*	-0.0002	0.0011	
	(0.000)		(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	
θ_{11}	0.0616*		0.1442*	0.0796*	0.1197*	0.0737*	0.0438*	
	(0.025)		(0.012)	(0.010)	(0.011)	(0.011)	(0.005)	
λ_{11}	-0.3410		0.8782*	0.9344*	0.9014*	0.9225*	0.9472*	
	(0.182)		(0.010)	(0.008)	(0.008)	(0.011)	(0.007)	
λ_{10}	0.0000*		0.0000*	0.0000	0.0000	0.0000*	0.0000*	
	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	
δ_{21}	0.0037		-3.0953*	0.1291*	0.0887*	-	-	
	(0.005)		(0.161)	(0.022)	(0.011)			
α_2	-0.0002		-0.0031*	0.0017*	0.0019*	0.0006	0.0013*	
	(0.000)		(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	
θ_{21}	0.0339*		0.1545*	0.0748*	0.1049*	0.0642*	0.0377*	
	(0.009)		(0.013)	(0.010)	(0.011)	(0.011)	(0.005)	
λ_{21}	0.9519*		0.8711*	0.9369*	0.9153*	0.9229*	0.9524*	
	(0.013)		(0.010)	(0.009)	(0.008)	(0.013)	(0.007)	
λ_{20}	0.0000		0.0000*	0.0000	0.0000*	0.0000*	0.0000*	
	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	
Log likel.	7151		6516	5446	6009	5988	6128	
AIC	-14279		-13011	-10869	-11999	-11957	-12238	
BIC	-14220		-12957	-10815	-11950	-11908	-12194	

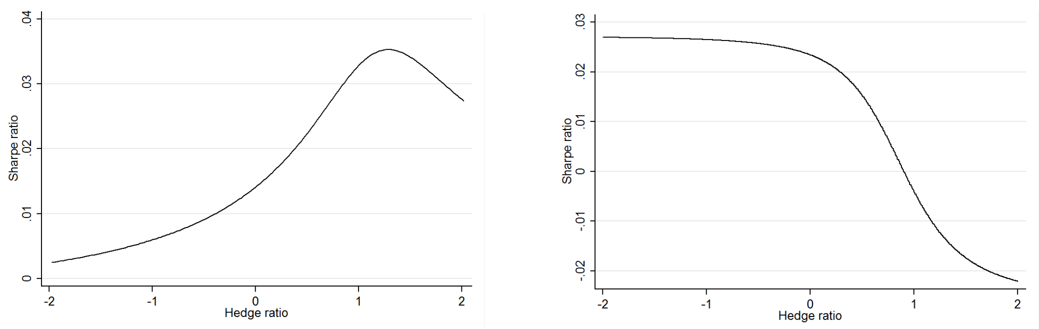
*significant at 5% level

5.2.2 Estimated Hedge Ratios

We estimate 25 different hedge ratios for each commodity - 8 types of hedge ratios are obtained through econometric analysis and 17 hedge ratios are computed. Strictly speaking, the computed group includes only 4 different types of hedge ratios as the MEG (Gini) hedge ratio and the GSV hedge ratio depend on the risk parameters and we estimate the MEG and GSV hedge ratios for five different risk parameters and compare the results. Further, there are two approaches for calculation of the GSV hedge ratio and we employ both of them.

There are some missing hedge ratios due to reasons described in the previous section and due to instability of the Sharpe hedge ratio results. Maximal Sharpe ratio cannot be always found in a reasonable interval of hedge ratios,[6] as depicted in the Figure 5.1. The first figure shows a graph of Sharpe ratio of Soybeans calculated on observations 1-1000 with a peak at approximately 1.1, whereas the second figure represents the Sharpe ratio graph of the same commodity based on observations 350-1350. In the latter case, the maximal Sharpe ratio is not found on the given interval of hedge ratios and increases with decreasing hedge ratio. This strange behaviour implies a high volatility in the hedge ratios calculated by the formula based on Sharpe ratio and we rather omit these problematic commodities.

Figure 5.1: Dependence of Sharpe ratio on hedge ratio



An overview of the in-sample hedge ratios can be found in Table 5.14, the out-of-sample results are presented in Table 5.15. Further, we provide graphs of all constant hedge ratios for each commodity presented in the Appendix. To compare the constant hedge ratios and the time-varying hedge ratios obtained through the bivariate GARCH estimation, we plot only the main constant hedge ratios and the bivariate GARCH hedge ratios obtained through specified models

[6] We consider the interval (-2, 2).

to prevent the figures from looking overfull, the figures are presented later in this section. Comparisons of the simple and specified bivariate GARCH hedge ratios can be found in the Appendix as well. Beside the series of the bivariate GARCH hedge ratios, we use their averages in the comparative analysis. The out-of-sample graphical documentation includes graphs of the hedge ratios obtained by the rolling window method and graphs of averages of these ratios.

Table 5.14: Hedge ratio - in-sample

HR, in-sample	Beef	Coffee	Copper	Corn	Oil	Platinum	Soybeans	Wheat
OLS, sim	0.0431	-0.0032	0.9701	0.9691	1.0150	0.6976	0.9910	1.1605
OLS, spec	0.0544	0.0246	0.9738	0.9728	-	0.6747	0.9951	1.1621
ECM, sim	0.0475	-	0.9746	0.9703	1.0275	0.6989	0.9901	1.1636
ECM, spec	0.0596	-	0.9774	0.9777	-	0.6827	0.9941	1.1632
GARCH, sim	0.0398	-0.0584	-	1.0857	1.0028	0.6904	1.0072	1.2042
GARCH, spec	-	0.0326	-	1.0830	1.0035	0.6833	0.9945	-
bGARCH, sim, a	0.0465	-0.0081	0.9642	0.9565	0.9956	0.7021	0.9790	1.1340
bGARCH, spec, a	0.0573	-	0.9823	0.9766	0.9939	0.7016	0.9782	-
Sharpe	-	-	0.8448	-	1.0398	-	-	1.2871
Gini, v=1.5	0.0434	-0.0289	0.9681	0.9639	1.0274	0.6773	0.9837	1.1498
Gini, v=2	0.0425	-0.0275	0.9717	0.9704	1.0159	0.6874	0.9887	1.1603
Gini, v=5	0.0424	-0.0011	0.9786	0.9772	0.9953	0.7111	0.9981	1.1778
Gini, v=10	0.0413	0.0192	0.9799	0.9798	0.9804	0.7399	1.0052	1.1896
Gini, v=20	0.0342	0.0335	0.9800	0.9862	0.9626	0.7671	1.0157	1.2100
Gini2, v=1.5	0.0313	-0.0023	0.9988	1.0450	1.0116	0.6945	1.0111	1.1416
Gini2, v=2	0.0302	-0.0023	0.9993	1.0499	1.0123	0.7039	1.0124	1.1436
Gini2, v=5	0.0348	0.0160	0.9995	1.0539	1.0201	0.7234	1.0107	1.1573
Gini2, v=10	0.0409	0.0319	0.9978	1.0509	1.0295	0.7368	1.0032	1.1733
Gini2, v=20	0.0541	0.0451	0.9904	1.0308	1.0427	0.7472	0.9896	1.2012
GSV, α=1	0.0424	-0.0259	1.0000	1.0519	1.0069	0.6966	1.0143	1.1353
GSV, α=2	0.0593	-0.0023	0.9591	0.9794	1.0381	0.7193	0.9936	1.1811
GSV, α=3	0.0766	-0.0266	0.8195	0.8031	1.0381	0.7106	0.9883	1.2294
GSV, α=4	0.0939	-0.0957	0.7321	0.6997	1.0752	0.6707	0.9845	1.3081
GSV, α=5	0.1065	-0.1000	0.6882	0.6471	0.9804	0.6056	0.9627	1.4000
VaR	0.0413	-0.0004	1.0002	1.0366	1.1046	0.7289	1.0345	1.1877

The in-sample results do not allow for making generalizations of the impact of the estimation type on the value of hedge ratio, but we describe the features that hold for most of the cases:

1. Hedge ratio increases with the level of specification of the econometric models, from the lowest value for the simple OLS to the highest values for the specified error correction models.
2. The simple bivariate GARCH model reports the lowest hedge ratios compared to the univariate econometric models.
3. The MEG hedge ratios obtained through the two described methods differ.
4. The VaR hedge ratios are among the highest ones.

Table 5.15: Hedge ratio - average of daily HR, out-of-sample

HR, out-of-sample	Beef	Coffee	Copper	Corn	Oil	Platinum	Soybeans	Wheat
OLS, sim	0.0434	0.0121	0.9861	0.8970	1.0127	0.6813	0.9724	1.0861
OLS, spec	0.0519	0.0224	0.9860	0.8919	-	0.6555	0.9760	1.0886
ECM, sim	0.0444	-	0.9863	0.8981	1.0207	0.6881	0.9720	1.0875
ECM, spec	0.0553	-	0.9866	0.9021	-	0.6638	0.9754	1.0850
GARCH, sim	0.0378	-0.0159	-	1.0208	1.0030	0.6947	0.9697	1.1045
GARCH, spec	-	0.0134	-	1.0302	1.0043	0.6801	0.9794	-
bGARCH, sim	0.0502	-0.0111	0.9840	0.9030	0.9405	0.6553	1.0122	0.9803
bGARCH, spec	0.0634	-	0.9705	0.8847	0.9390	0.6250	1.0237	-
Sharpe	-	-	0.8606	-	1.1272	-	-	1.5383
Gini, v=1.5	0.0433	-0.0021	0.9834	0.9064	1.0213	0.6645	0.9739	1.0866
Gini, v=2	0.0431	-0.0048	0.9825	0.9148	1.0133	0.6710	0.9751	1.0930
Gini, v=5	0.0429	0.0107	0.9832	0.9229	0.9986	0.6877	0.9738	1.0978
Gini, v=10	0.0432	0.0251	0.9858	0.9156	0.9874	0.7104	0.9760	1.0978
Gini, v=20	0.0393	0.0299	0.9903	0.8971	0.9738	0.7356	0.9804	1.1034
Gini2, v=1.5	0.0345	0.0135	0.9998	1.0137	1.0085	0.6807	1.0037	1.0734
Gini2, v=2	0.0341	0.0135	1.0001	1.0184	1.0087	0.6859	1.0044	1.0751
Gini2, v=5	0.0399	0.0180	1.0003	1.0141	1.0134	0.6968	1.0005	1.0883
Gini2, v=10	0.0442	0.0182	1.0000	0.9961	1.0198	0.7056	0.9919	1.1046
Gini2, v=20	0.0511	0.0242	0.9984	0.9407	1.0280	0.7085	0.9750	1.1219
GSV, α=1	0.0357	0.0175	1.0004	1.0254	1.0067	0.6759	1.0063	1.0744
GSV, α=2	0.0544	0.0128	0.9868	0.9005	1.0255	0.6921	0.9754	1.1153
GSV, α=3	0.0692	-0.0035	0.9402	0.7058	1.0255	0.6866	0.9312	1.1349
GSV, α=4	0.0919	-0.0455	0.9235	0.6053	1.0366	0.6535	0.8745	1.1321
GSV, α=5	0.1168	-0.0857	0.9845	0.5563	0.9810	0.5933	0.8081	1.1410
VaR	0.0344	0.0062	1.0019	1.0113	1.0673	0.6993	1.033	1.1161

The average out-of-sample hedge ratios listed in Table 5.15 are generally lower than the in-sample hedge ratios, even though the change of correlation structure of returns is not as clear. The above mentioned statements hold also for the out-of-sample hedge ratios, but the claim about the bivariate GARCH hedge ratio is significantly challenged by the Soybeans example, where the bivariate GARCH hedge ratios are much higher than any other econometric hedge ratio.

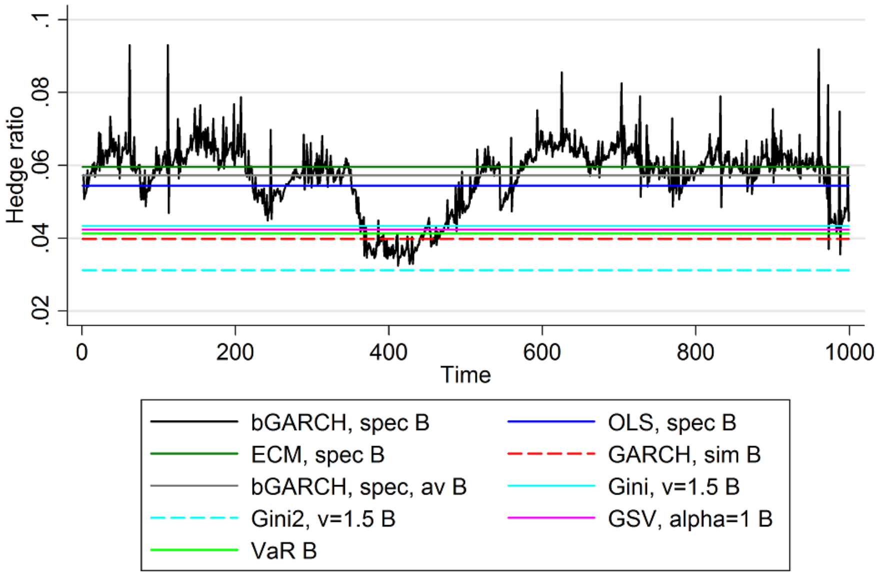
The efficiency of the hedge ratios is measured by employing four different methods: in-sample hedge ratios, out-of-sample daily changing hedge ratios, out-of-sample weekly changing hedge ratios, and average out-of-sample hedge ratios. A table summarizing all results would be too complex, so we present the outcomes for each commodity separately, the tables can be found as Tables A.1 to A.8 in the Appendix. In addition to the tables, we present the results of the efficiency analysis in graphs included in the subsections describing outcomes for each commodity.

Table 5.16: Numbering of hedge ratio types

Type	Hedge ratio
1	Naive
2	OLS, simple
3	OLS, specified
4	ECM, simple
5	ECM, specified
6	GARCH, simple
7	GARCH, specified
8	bGARCH, simple
9	bGARCH, specified
10	bGARCH, simple, av.
11	bGARCH, specified, av.
12	Sharpe
13	Gini, v=1.5
14	Gini2, v=1.5
15	GSV, α=1
16	VaR

The results differ for various commodities and cannot be generalized. Hence, we provide a more detailed analysis of the hedge ratios and their efficiency for individual commodities. In the efficiency graphs, we use a numbering of the hedge ratio types provided in Table 5.16. Moreover, results of the MEG and GSV hedge ratios for different risk parameters are analysed in a special subsection. We use the MEG and GSV hedge ratios with the lowest risk parameters, characterizing hedgers close to risk neutrality, to compare these types of hedge

Figure 5.2: Beef - overview of main in-sample HR



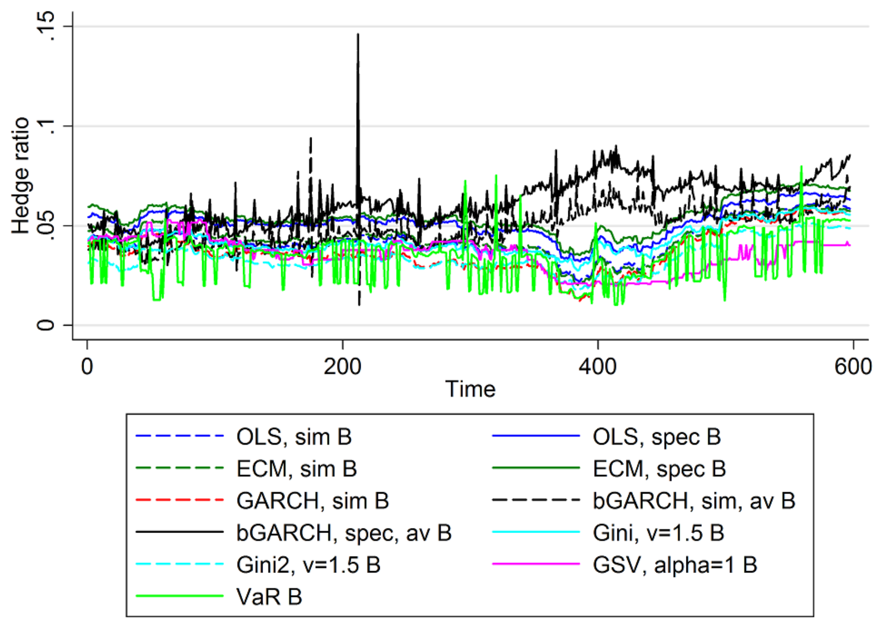
ratios with the others. Although we consider rather risk neutral hedgers (not infinitely risk averse), the hedge ratios obtained through different approaches should be close due to the nearly zero mean returns.

Beef

As noted before, we have chosen the futures whose returns poorly correlate with the spot returns, which is not appropriate for hedging of the spot position. This fact is reflected in the quality of outcomes as the models are not well specified. In spite of the unreliability of the outcomes, we provide a brief discussion as the coefficients estimating the hedge ratios are significantly different from zero in all models.

Considering the in-sample analysis, the hedge ratios can be divided into two groups based on their values: the specified versions of OLS, the ECM and bivariate GARCH models (in average) provide high hedge ratios approaching 0.06, and the other estimators result in the values between 0.04 and 0.05, as shown in Figure B.5. Figure 5.2 displays that the bivariate hedge ratio fluctuates along the first group of the hedge ratios; but it drops in the range of 380 (November 11, 2008) to 500 (May 1, 2009), which is associated with the higher volatility of the returns in this period. The hedge ratios obtained through the simple and specified bivariate GARCH models have very similar patterns, but the “specified” hedge ratios are higher (the correlation between the two hedge ratios is 87%) as depicted in Figure B.3.

Figure 5.3: Beef - overview of out-of-sample HR



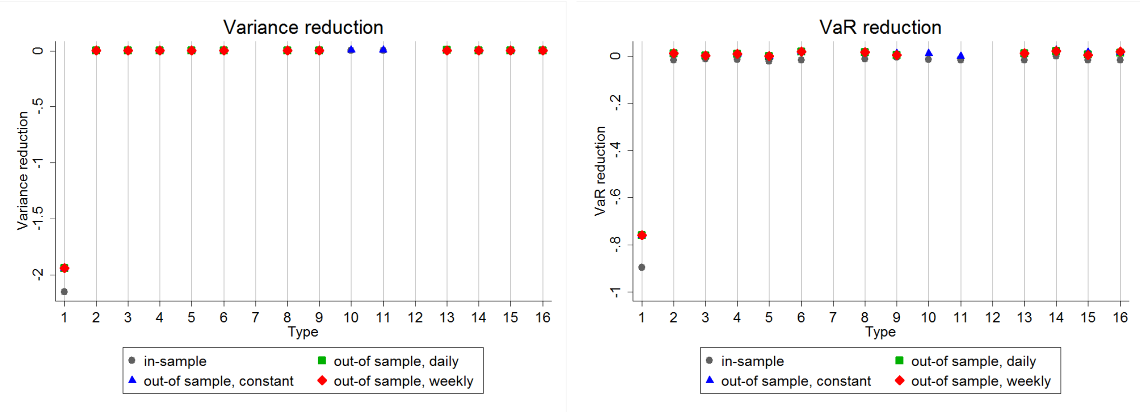
The hedge ratios in the out-of-sample analysis are obtained through the rolling window approach and thus vary over time. The x-axis in Figure 5.3 defines the out-of-sample period for which the given hedge ratio should be used. Most of the hedge ratios are relatively constant, although they slightly decrease and then increase in the second half of the sample. This is connected to the changes in correlation of the spot and futures returns.[7] The correlation is firstly stable, but there is a drop followed by an increase in the second half of the out-of-sample period, as shown in Figure B.4. All hedge ratios except for the bivariate GARCH hedge ratios are strongly autocorrelated, supporting the hypothesis that it would be appropriate to use constant hedge ratios.

The bivariate GARCH hedge ratios resulting from the rolling window method are less volatile than the in-sample bivariate hedge ratios. Interestingly, they develop differently than the other hedge ratios in time. Specifically, we can observe the opposite patterns - a growth followed by a decrease - in the second half of the sample.

Looking at the average out-of-sample hedge ratios in Figure B.6 in the Appendix , we find that the mean specified bivariate GARCH hedge ratio equals to 0.64, which is much higher than the other mean hedge ratios ranging between 0.55 and 0.35. The ranking is similar as in the in-sample analysis:

[7] For estimation of hedge ratio for $t+1$, we use observations from the range $t-1000$ to t.

Figure 5.4: Beef - reduction in variance and VaR



the specified bGARCH, OLS, and ECM hedge ratios are the highest, followed by the simple bGARCH, OLS, and ECM hedge ratios, and the lowest hedge ratios are obtained through the numerical approaches and the simple GARCH model. Most of the hedge ratios are slightly lower than in the case of in-sample analysis.

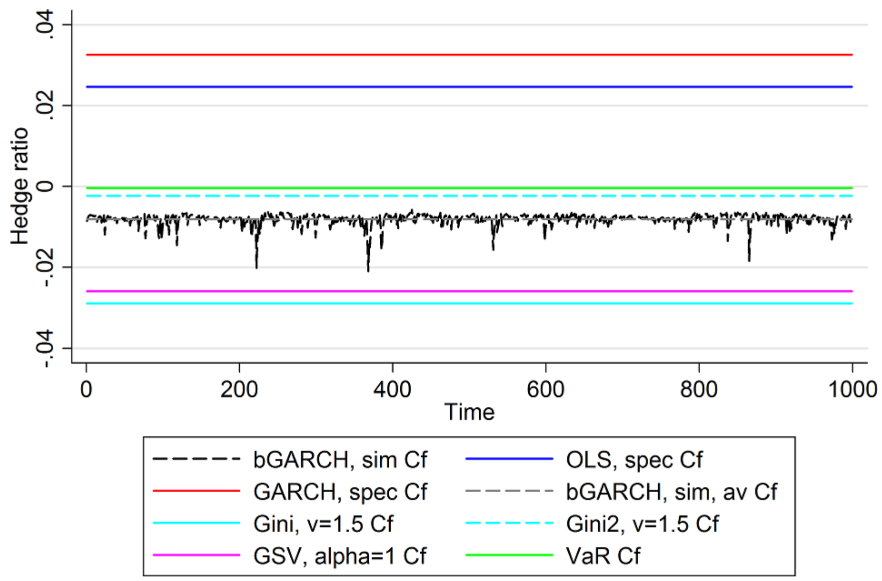
The efficiency analysis recorded in Figure 5.4 confirms that the chosen futures poorly match the spot position. The worst performing hedge strategy is clearly the naive hedge ratio equal to 1, which is in the case of poorly correlated spot and futures returns indeed a badly chosen plan. An overview of the hedging efficiency can be found in Table 5.11 in the Appendix and an overall summary including mean revenues, variance, VaR, skewness and kurtosis and their reduction, using different hedge strategies, is listed in Tables A.17 and A.18 in the Appendix.

Although the returns maximization is not the main subject when searching for the optimal hedge ratio, we can briefly evaluate the impact of hedging on the mean returns represented in Tables A.17 and A.18 in the Appendix. Again, we discuss only the GSV and MEG hedge ratios with the lowest risk parameter. As the hedge ratios are close the zero, the effect is negligible and the mean returns are very close to 0; the bGARCH hedge ratio has the most significant positive effect. In general, the effects are positive but weak.

Coffee

The Coffee hedge ratios analysis faces the identical problem as the Beef hedge ratio analysis - poorly and even negatively correlated spot and futures returns resulting from inappropriate choice of the futures for hedging. Further, the data shows no cointegration, and the hedging coefficients in the OLS models are insignificant. The GARCH coefficients are significant, but the values given by the specified and simple models greatly differ - the simple GARCH implies a negative hedge (-0.06), whereas the specified GARCH suggests a positive hedge (0.04), so the span of possible hedge ratios is wide, as presented in Figure B.7. The bivariate GARCH fluctuates along -0.01 and, it does not intersect any of the other hedge ratios, unlike the bGARCH hedge ratios of the other commodities, which approves that the span of the hedge ratios is large and the hedge ratio estimations are unreliable.

Figure 5.5: Coffee - overview of main in-sample HR



Most of the out-of-sample hedge ratios are increasing, the specified GARCH and VaR hedge ratios are decreasing, and the simple bGARCH hedge ratio stays constant with low volatility (see Figure 5.6). The averages of the out-of-sample hedge ratios in Figure B.8 in the Appendix take values between -0.02 and 0.02, so the interval narrows. However, the results of the hedging effectiveness show that the hedging has a null effect for all hedging strategies except for the naive one, which has a strongly negative effect. An overview of the efficiency results is presented in Table A.2 in the Appendix and an overall summary of the hedging results is summed up in Tables A.19 and A.20 in the Appendix. Considering the returns, the effect of hedging is negligible.

Figure 5.6: Coffee - overview of out-of-sample HR

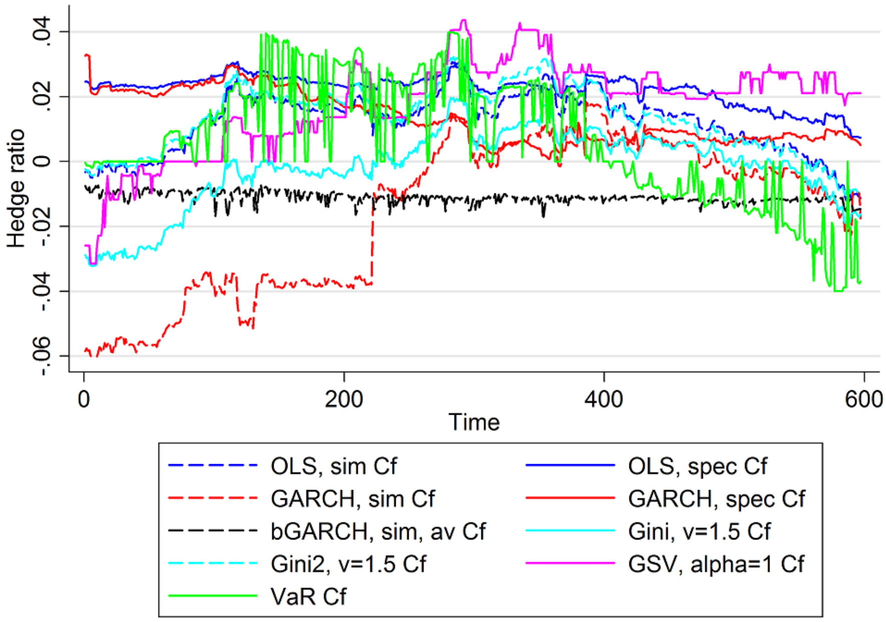
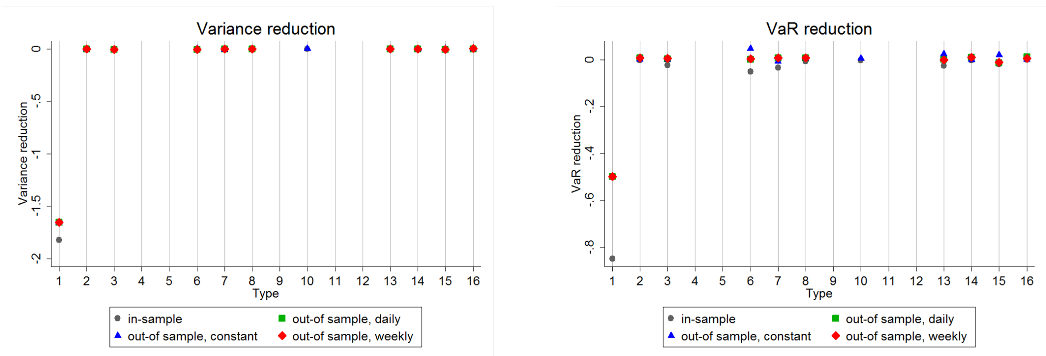


Figure 5.7: Coffee - reduction in variance and VaR



Copper

The Copper spot and futures prices returns are highly correlated (the correlation coefficient is approximately 95%) and the values of Adjusted R^2 of the econometric models are highest of all the models; the estimated hedge ratios should be close to one and the hedging should be highly efficient.

Most of the hedge ratios are in the interval (0.96, 1) and the highest values are obtained through the MEG 2, GSV and VaR methods. Recall, that the MEG 2 and MEG 1 hedge ratios should be nearly identical if their values are lower than 1. In our case, the MEG 1 hedge ratio is smaller and takes value of 0.968, so it is probable that the two approaches for the MEG hedge ratio computation have generally different results. We examine this hypothesis in Section 5.2.3. The Sharpe hedge ratio is an outlier with value of 0.84, as presented in Figure B.9 in the Appendix. Results of the econometric models are very close, yet the GARCH models do not converge for some sub-samples and hence we do not provide the GARCH hedge ratios. The specified bivariate GARCH hedge ratio fluctuates along the value estimated by the econometric models, and at one point it decreases to the value of the Sharpe hedge ratio as illustrated in Figure 5.8. Even though the patterns in the simple and specified bivariate GARCH hedge ratios seem to be very similar (see Figure B.11 in the Appendix), the two hedge ratios series are nearly uncorrelated, so the efficiency results of these two hedge ratios may differ.

The correlation between the spot and futures returns slightly increases across the sample (from 0.96 to 0.97 with a peak of 0.98), but the changes are negligible - we would arguably not be able to track them in the out-of-sample hedge ratio results. Looking at Figure 5.9 depicting the out-of-sample hedge ratios, we find that the most time-varying hedge ratio is the Sharpe hedge ratio; the bivariate GARCH hedge ratios are generally stable (there are three significant deflections reaching up to 1.5, but the hedge ratios return back to 1 quickly), and the other hedge ratios seem to be nearly constant, taking values close to 1. The constancy is supported by high autocorrelation of all hedge ratios.

The average out-of-sample hedge ratios are nearly identical as the constant in-sample hedge ratios (see Figure B.10 in the Appendix), so the efficiency of the daily changing hedge ratios and the constant hedge ratios should be close. The MEG 2, GSV and VaR hedge ratios take values close to 1 and the average Sharpe hedge ratio is slightly higher than 0.85.

Figure 5.8: Copper - overview of main in-sample HR

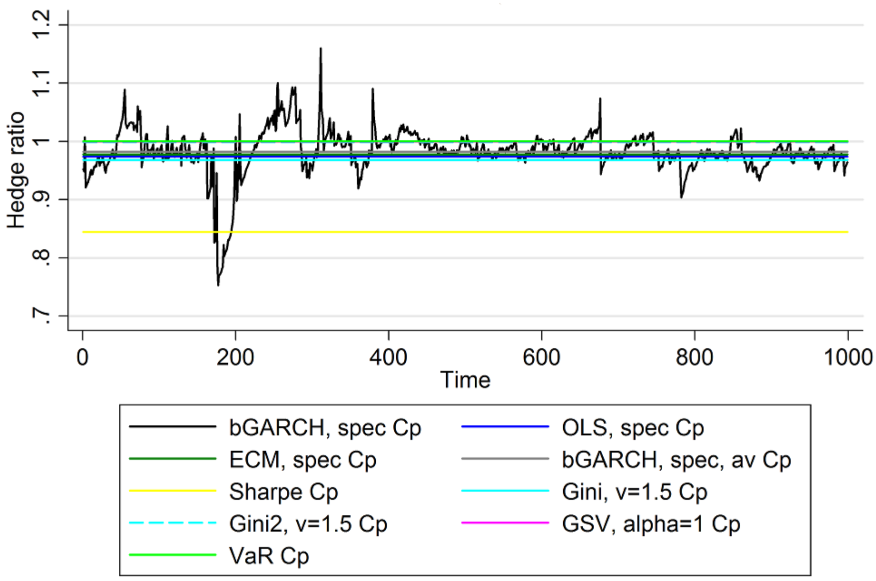


Figure 5.9: Copper - overview of out-of-sample HR without Va

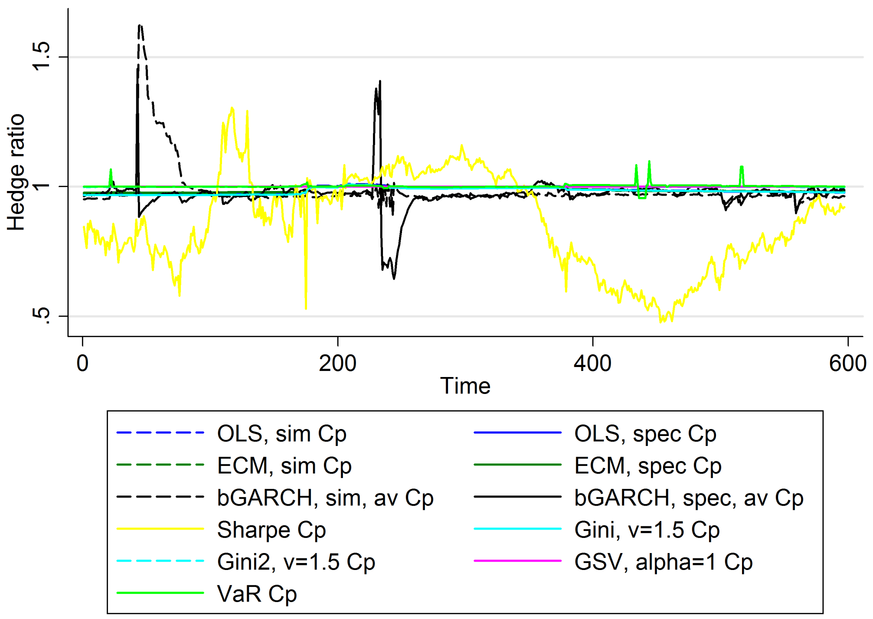
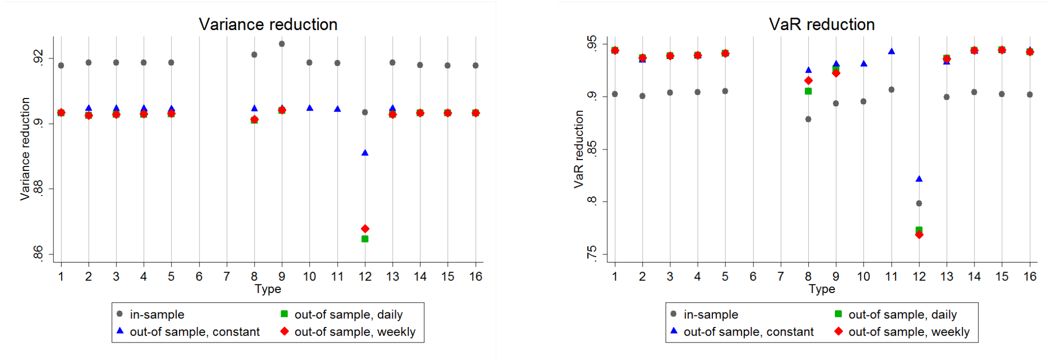


Figure 5.10: Copper - reduction in variance and VaR



The evaluation of the hedge ratio efficiency can be found in Figure 5.10. The hedging decreases VaR and variance approximately by 90%. While the hedging performance in terms of variance is best in the case of the in-sample analysis, VaR is more successfully reduced in the out-of-sample hedging.

The Sharpe hedge ratio is the least efficient in terms of both variance and VaR. Although the econometric hedge ratios are not equal to 1, the hedging effectiveness of the naive hedging is close to the performance of the OLS and ECM models. The OLS and ECM models provide nearly identical results for all types of the out-of-sample hedging and also for VaR and variance, which is caused by the fact that the daily changing hedge ratios are nearly constant. The average bivariate GARCH models are more successful than the time-varying bivariate GARCH models in terms of VaR and less successful in term of variance; the constant hedging reduces variance and VaR more than the daily or weekly changing hedge ratios. The specified bivariate GARCH hedge ratio outperforms the simple one. We can conclude that the bGARCH hedge ratio does not significantly outperform the other types of hedge ratios. The computational hedge ratios (MEG 2, GSV and VaR) behave similarly as the OLS and ECM hedge ratios, and the daily/weekly changing hedge ratios are as successful as the constant hedging. The similar performance of the constant and time-varying hedging supports the constant hedge ratio hypothesis. In the case of this combination of spot position and futures, we would recommend to use the naive hedging, as it is the least demanding regarding calculation; a hedging company has to control only the changes in correlation of spot and futures returns.

An overview of the hedging efficiency can be found in Table A.3 in the Appendix and an overall summary of the hedging for Copper is presented in

Tables A.21 and A.22 in the Appendix.

The effect of the in-sample hedging on the mean returns is negative, whereas the impact of the out-of-sample hedging is positive. Considering the in-sample returns, the hedging reduces the mean returns by 56% on average. Performance of most of the hedge ratios is comparable, only the simple bGARCH and Sharpe hedge ratios stand out with returns reduction of 50%, which is probably caused by the fact that these two hedge ratios are, on average, the lowest ones. The out-of-sample impact is stronger and it turns negative mean returns to positive. The best performing hedge ratio is the VaR hedge ratio - it provides a 120% increase in the mean returns on average. (The VaR hedge ratio is the highest, so its impact is the strongest. As the hedge ratios are nearly constant, the value plays a main role in the mean returns effect; hence, we mention it only briefly at the end of each subsection.) The naive hedging performs comparable with the average as it increases the out-of-sample returns by 113%.

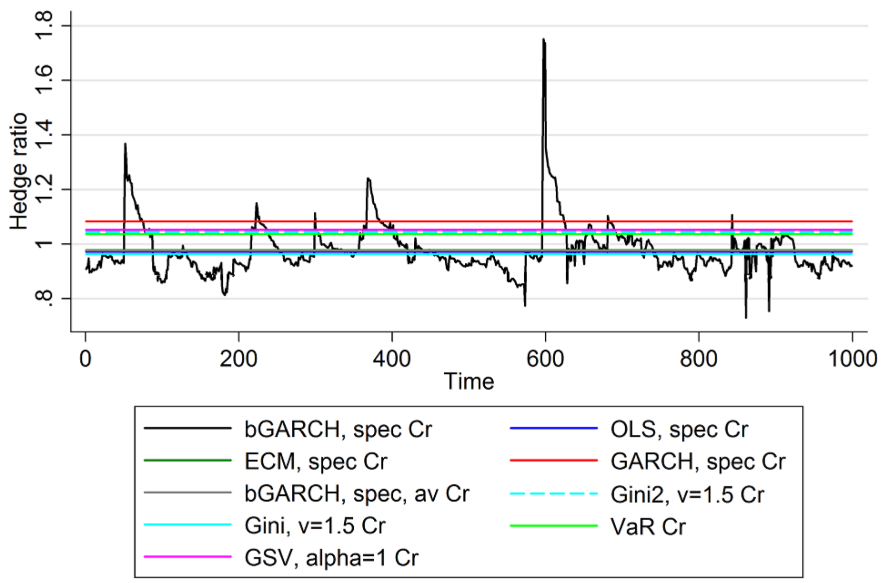
Corn

Corn shows relatively strong correlation in the spot and futures returns but the correlation decreases with time (from 0.85 to 0.8). The values of Adjusted R^2 of econometric models are not as large as for Copper but suggest that the models are still well specified. We suppose that the hedge ratios will be between 0.8 and 1 and the hedging efficiency will be slightly lower than for Copper.

The estimated hedge ratios create three groups: one consists of the GARCH hedge ratios reaching value 1.08, the second group includes the MEG 2, VaR, and GSV hedge ratios as in the Copper case with values around 1.05, and they are followed by all other econometric hedge ratios with values in range of (0.95-0.98) as depicted in Figure B.13 in the Appendix. The specified bivariate GARCH hedge ratio fluctuates along all three groups taking values between 0.8 and 1.2 with two peaks reaching 1.4 and 1.8 as shown in Figure 5.11. The simple and specified bivariate GARCH hedge ratios are strongly correlated and follow very similar patterns. (See Figure B.12 in the Appendix.) Hence, we suppose that the hedging strategies would have identical efficiency results.

Examining the out-of-sample daily changing hedge ratios, we find that the GARCH hedge ratios come closer to the second group during the time, the bivariate GARCH hedge ratios remain volatile (unlike for Copper) with similar patterns, and the other hedge ratios, except for VaR, seem to be nearly constant with a slight decrease in time, related to the drop in correlation. The

Figure 5.11: Corn - overview of main in-sample HR



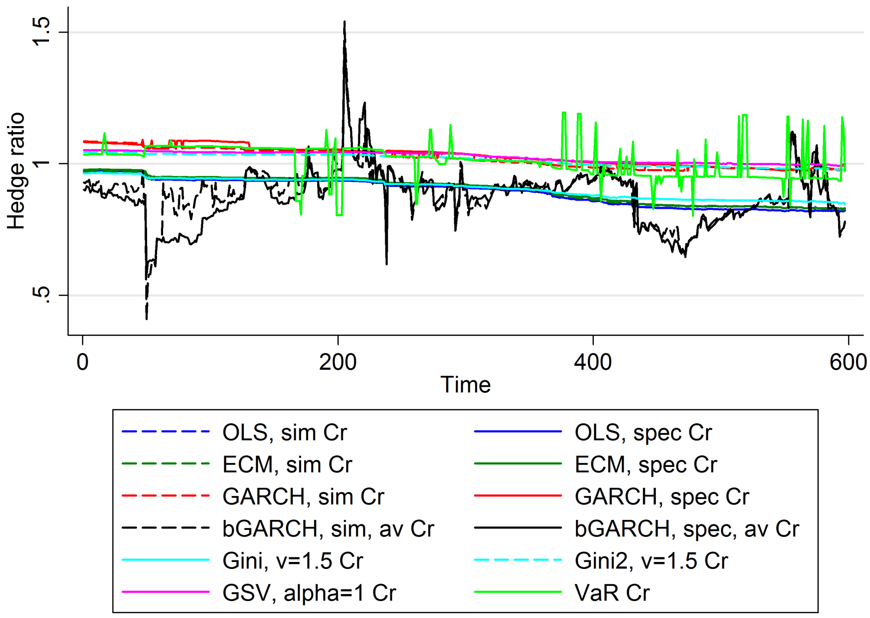
autocorrelation of all hedge ratios is very high, favouring constant hedge ratios. The described features can be found in Figure 5.12.

The means of the out-of-sample hedge ratios shown in Figure B.14 in the Appendix confirm that the hedge ratios remain in two groups - the first one is higher than the second one, the decrease compared to the in-sample results is caused by the drop in correlation.

The difference in the efficiency between the two groups of hedge ratios can be also found in Figure 5.13. The reduction in variance is larger than 70%, while the reduction in VaR is lower, taking values between 65% and 70% for the out-of-sample analysis (the in-sample analysis has better results with VaR reduction of app. 73%). So the hedging efficiency is worse than in the case of Copper as we supposed. The variance reduction reflects the values of Adjusted R^2.

In the terms of variance, the least successful are the GARCH hedge ratios, followed by the MEG 2, GSV and VaR signalling that the hedge ratios are probably overestimated. These hedge ratios perform better than the others in case of the in-sample VaR reduction, but the out-of-sample VaR reduction is poor again. The naive hedge ratio works well in the in-sample analysis, where it is comparable with the OLS and ECM hedging in both VaR and variance, but it significantly underperforms in the out-of-sample efficiency. The OLS and ECM models provide stable results of approximately 75% reduction in variance

Figure 5.12: Corn - overview of out-of-sample HR



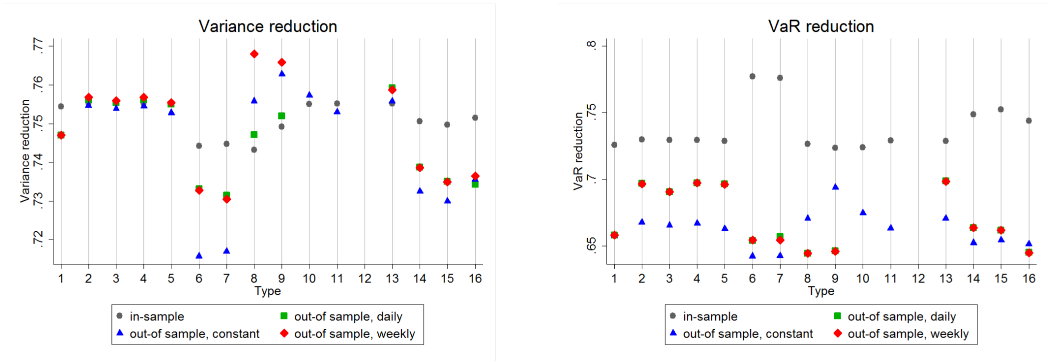
for all four types of variance efficiency analysis, and they reach the highest VaR reduction for the changing hedge ratios and an average VaR reduction for the constant hedge ratios. Good and stable results are provided particularly by the MEG 1 hedge ratio.

The bivariate GARCH hedge ratios underperform in the in-sample and daily changing variance analysis, where the best performing hedge ratios are the naive, OLS, ECM and average bGARCH hedge ratios, but it strongly outperforms the other hedge ratios in the weekly changing and constant hedge ratios variance efficiency. The performance of bGARCH hedge ratios in terms of the VaR reduction is comparable to the OLS, ECM, and naive approaches for the in-sample analysis, they underperform in the daily and weekly changing hedge ratios efficiency and provide the best results for the constant hedging. The specified bGARCH slightly outperforms the simple bGARCH in terms of the variance reduction.

The variance reduction supports the constant hedge ratio hypothesis, but the VaR reduction suggests the opposite. The efficiency analysis does not have a clear winner, but, based on the simplicity of estimation and stable results, we would recommend to use OLS hedging for Corn.

An overview of the efficiency results can be found in Table A.4 in the Appendix and an overall summary is presented in Tables A.23 and A.24 in the

Figure 5.13: Corn - reduction in variance and VaR



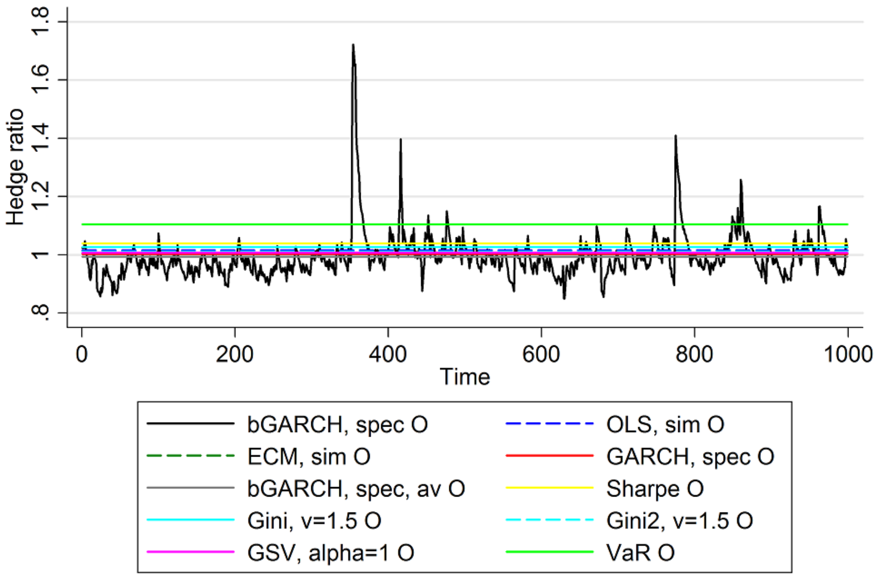
Appendix. The impact of the hedging on the mean returns is similar as in the case of Copper - positive for the out-of-sample hedging and negative for the in-sample-hedging, but the effect is much weaker. The in-sample performance of all hedge ratios is close to 21% of returns reduction. The out-of-sample returns increase, yet they stay negative. The performance differs across the types of hedging; constantly good results are given by the simple GARCH and simple bGARCH models with returns increase by approximately 36%. The simple OLS performance is ordinary, taking values of 29% in the out-of-sample returns growth.

Oil

The Oil's spot and futures spot returns are strongly correlated and the correlation increases through the observed period from 91% to 98%; this growth may be observable in the out-of-sample analysis graphs. The econometric analysis suggests that a specification of the OLS and ECM models does not improve the fitting, and the Adjusted R^2 is above 0.8 for both basic models. Again, we suppose that the reduction in the efficiency will be significant (close to the case of Copper) and hedge ratios will take values close to 1.

The in-sample hedge ratios are mixed up differently than in the cases of Copper and Corn though all of them have values larger or very close to 1 (see Figure B.15 in the Appendix). The highest hedge ratio is the VaR hedge ratio, followed by the Sharpe hedge ratio. Other hedge ratios create a group taking values between 0.99 and 1.03. Figure 5.11 includes the time-varying specified bGARCH as well. The bGARCH hedge ratios fluctuate along the above mentioned group of hedge ratios, but it regularly reaches the VaR hedge ratio as well. Moreover, there are several peaks with values approaching 1.4 and

Figure 5.14: Oil - overview of main in-sample HR



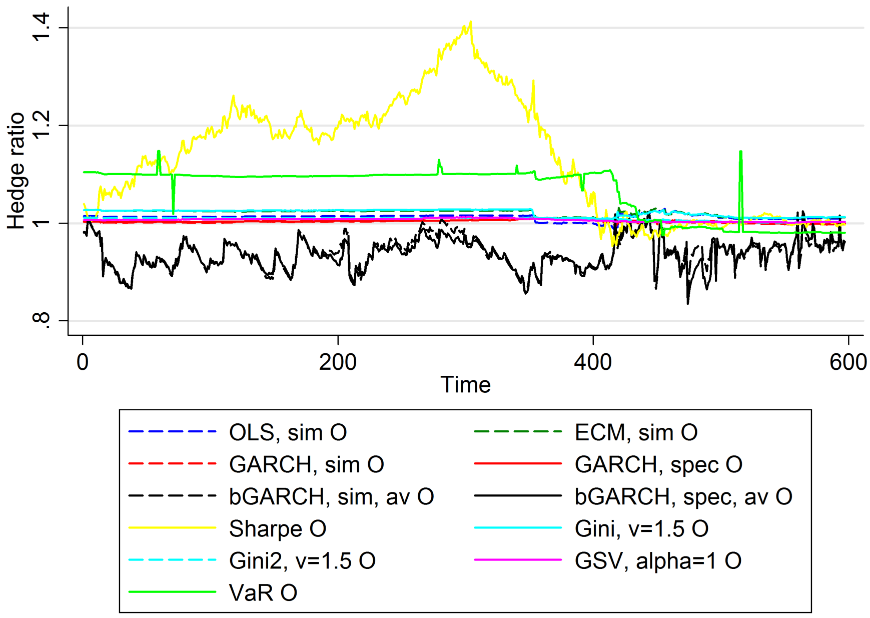
even 1.7. The simple and specified bGARCH hedge ratios have similar patterns and are strongly correlated, so their performance results shall be close.

The out-of-sample analysis shows that the bGARCH hedge ratio's amplitude is quite small; further, the bGARCH hedge ratios are lower than 1 and hardly ever reach the level of the other hedge ratios. The Sharpe hedge ratio, which gradually increases to the 1.4 value and then drops back to 1, is the most extreme hedge ratio. A similar drop can be observed in the VaR hedge ratio. Both of the drops are probably caused by the increase in returns' correlation. The other hedge ratios stay cumulated around 1 and seem to be constant, which is supported by strong autocorrelation. The features are shown in Figure 5.15.

The average Sharpe hedge ratio takes value of 1.123 and reaches the highest average value, replacing the VaR hedge ratio compared to the in-sample results. The ranking and values of the other hedge ratios remain nearly unchanged except for the bGARCH hedge ratio, which decreases to 0.94. (See Figure B.16 in the Appendix.)

Efficiency analysis is presented in Figure 5.16 and Table A.5 in the Appendix. Further, an overall summary can be found in Tables A.25 and A.26 in the Appendix. The hedge ratios provide much larger variance and VaR reduction in the out-of-sample analysis than in the in-sample analysis. The in-sample variance reduction is approximately 82%, while the out-of-sample

Figure 5.15: Oil - overview of out-of-sample HR VaR

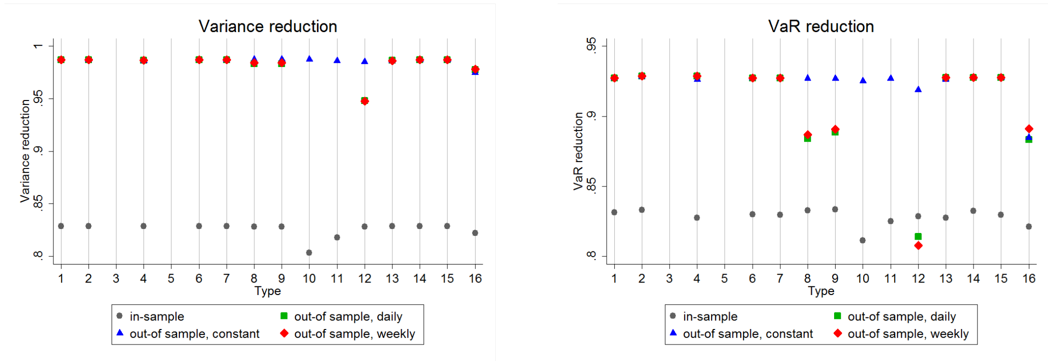


reduction reaches 98%. The in-sample VaR reduction is 82% as well, but the out-of-sample reduction is smaller than the variance reduction, taking values of 92%. The in-sample variance reduction is close to the Adjusted R^2 values again.

All the hedge ratios provide roughly the same in-sample variance reduction, only the averages of bGARCH hedge ratios are slightly worse. The out-of-sample variance reductions are comparable as well, the only outlier is the Sharpe hedge ratio, with the daily and weekly changing hedge ratios providing only 95% variance reduction. Results for the in-sample VaR reduction are identical, and the out-of-sample results lower the position of the bGARCH, Sharpe, and VaR hedge ratios, reaching values of 0.89 for the bGARCH and VaR hedge ratios and only 0.8 for the Sharpe hedge ratio (taking into account only the daily and weekly changing hedge ratios, the constant bGARCH and Sharpe hedge ratios perform well). The simple and specified bGARCH hedge ratios efficiency is nearly the same.

Both efficiency analyses support the hypothesis of a constant hedge ratio. The results do not provide any key for quality ranking of the hedging strategies, but, similarly as in case of Copper, we would recommend using the naive hedging as it is very simple and its performance is as good as the performance of other much more complicated hedge ratios.

Figure 5.16: Oil - reduction in variance and VaR



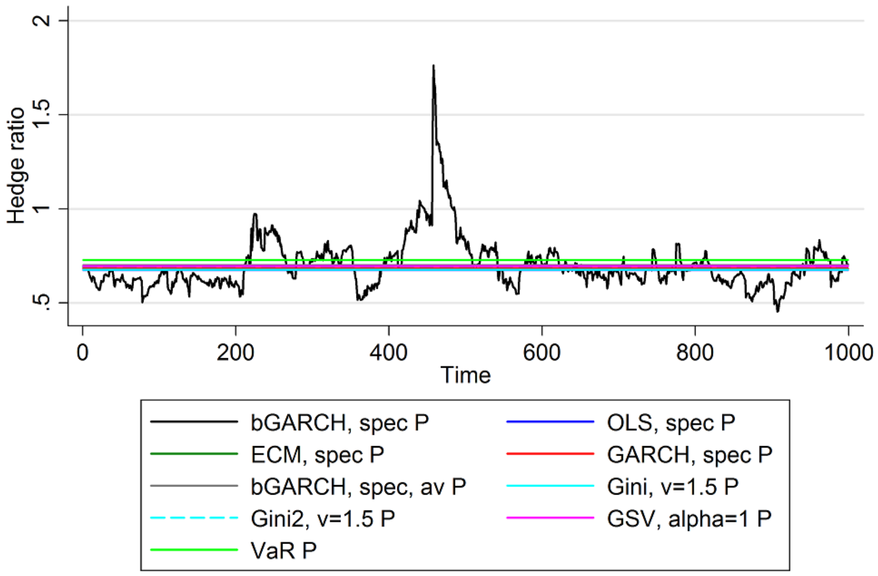
Tables A.25 and A.26 provide information about the impact of the hedging on the mean returns. The hedging increases the mean returns in both the in-sample and out-of-sample analyses, and while the increase in the in-sample hedging is negligible, the out-of-sample growth is considerable. The best performer is the VaR hedge ratio, increasing the mean return from -0.00002 to 0.0004 and 0.0002, respectively. The other hedge ratios do not fall behind and increase the mean returns to 0.00018 and 0.0009, which holds for the recommended naive hedge ratio as well. Finally, the mean returns are still very close to zero, so we assume that the increase will not have a larger effect on a decision of a hedging company.

Platinum

Platinum has, besides Coffee and Beef, the less correlated spot and futures returns, which will affect both values of hedge ratios and hedging effectiveness. Further, the correlation decreases from 0.74 to 0.68 and then returns to its original value. This drop may be observable in the out-of-sample hedge ratios. Adjusted R^2 significantly increases with level of specification from 0.53 to 0.73.

Figures B.19 in the Appendix and 5.17 show the results of the in-sample analysis; the first one depicts the constant hedge ratios and the other one captures the bGARCH hedge ratio as well. The VaR hedge ratio stands out with the value of 0.73, the other hedge ratios are concentrated between 0.705 and 0.675. Highest are the average bGARCH hedge ratios, followed interestingly by the simple econometric hedge ratios (for Copper and Corn, the simple hedge ratios were slightly lower than the specified ones), and the group is completed by the GSV and MEG 2 hedge ratios, with the MEG 2 hedge ratio being higher than the MEG 1 hedge ratio as in the case of Copper and Corn. The MEG 1

Figure 5.17: Platinum - overview of main in-sample HR



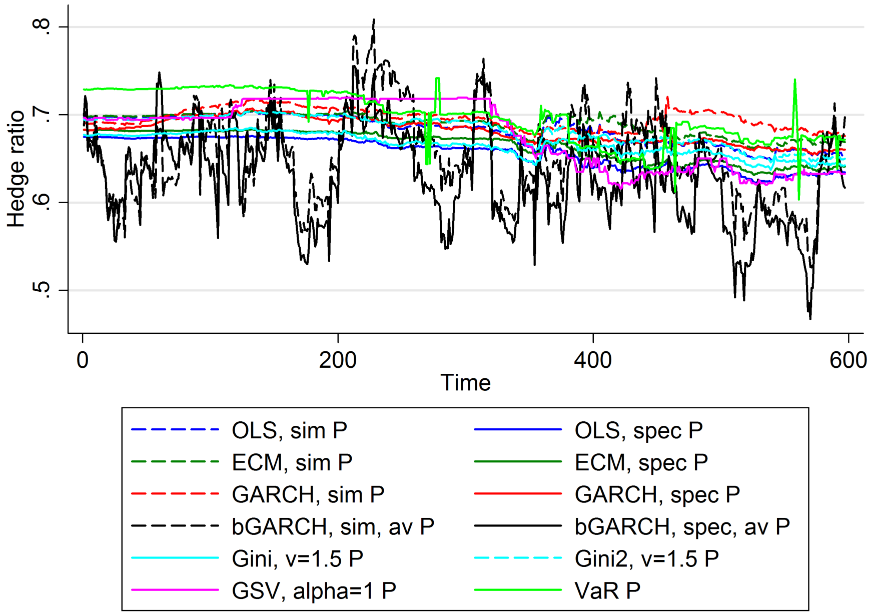
hedge ratio can be found among the specified hedge ratios that have the lowest values.

The specified bivariate GARCH hedge ratio takes on more extreme values than in the previous examples; mostly, it fluctuates along the constant hedge ratios but at one point it increases to 1.75 and then it drops back. The Platinum prices increased before the financial crisis and then significantly dropped between June and October 2008, which may relate to the financial crisis. In 2009 the Gold price was very high, so some investors used Platinum instead and the price increased again. This may relate to the peak at approximately 500th observation corresponding to April 2009. The simple and specified bivariate GARCH ratios look very similar and are highly correlated. Hence, the results of these two should correspond. (See Figure B.18 in the Appendix.)

Figure 5.15 sums up the out-of-sample hedge ratios. The bGARCH hedge ratios have the highest variance, but the hedge ratios are significantly lower than in the in-sample analysis, as all hedge ratios' values can be found in range from 0.45 to 0.8. The other hedge ratios seem to be constant in the first half of the sample, followed by a small drop and an increase for some of the hedge ratios, which relates to the changes in returns' correlation as described above. Nevertheless, the autocorrelation of hedge ratios is strong (including the bGARCH hedge ratios), supporting the constant hedge ratio hypothesis.

To compare the in-sample values and the average out-of-sample values of

Figure 5.18: Platinum - overview of out-of-sample HR

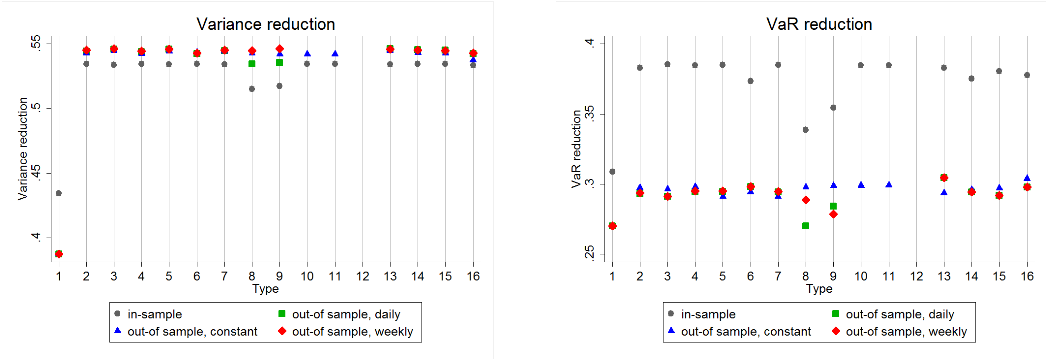


hedge ratios we look at Figure B.20 in the Appendix. The value of the VaR hedge ratio decreases and moves closer to the other hedge ratios. The simple hedge ratios still have higher values than the specified hedge ratios, but the ranking changed (1. GARCH, 2. ECM, and 3. OLS, while in the in-sample analysis it was 1. ECM, 2. OLS, and 3. GARCH). The gaps between the hedge ratios increased. The bivariate GARCH hedge ratios are the lowest ones (the average specified bGARCH is lower than 0.63). The ranking of the MEG 1, MEG 2, and GSV remains the same but the values shift down by approximately 0.01.

The lower correlation causes low efficiency of the naive hedging; otherwise, the variance reduction is approximately 54% for all hedge strategies (except for the naive hedge ratio) and all types of the efficiency examination. The variance reduction corresponds to the lower values of Adjusted R^2. The VaR reduction is higher for the in-sample analysis with values around 38% and the out-of-sample VaR reduction is approximately 30% only, as shown in Figure 5.19.

Although the in-sample constant hedge ratios vary between values 0.73 and 0.67, there are no differences in their in-sample effectiveness measured by variance. The same holds on for all of the out-of-sample hedge ratios, even though the range of the hedge ratios' values increases. Considering the in-sample anal-

Figure 5.19: Platinum - reduction in variance and VaR



ysis, the worst performing hedge ratios are the bivariate GARCH hedge ratios, but their out-of-sample variance performance is comparable to the performance of the other hedge ratios.

The VaR hedge ratio shows significant differences between the in-sample and out-of-sample analyses, but, disregarding the naive and the bGARCH hedge ratios, the results do not show significant differences between individual hedge ratios. The simple and specified OLS hedge ratios and the ECM and specified GARCH hedge ratios provide the same results, the simple GARCH underperforms in the in-sample hedging. The bivariate GARCH hedge ratios have a low efficiency in both the in-sample and out-of-sample analyses, only its performance in the constant out-of-sample analysis is comparable to the others. The MEG 1 provides the best results out of the computational hedge ratios and also for the daily and weekly changing hedge ratio in the out-of-sample analysis considering all hedge ratios. On the other hand, it slightly underperforms in the constant out-of-sample hedging.

The variance and VaR reduction is similar for the constant and time-varying hedging, which supports the hypothesis of the constant hedge ratio. The results do not significantly favour any of the examined hedge ratios and the complex econometric hedge ratios rather underperform. Comparing the complexity of calculation and results, we recommend to use the basic OLS regression for estimation of the optimal hedge ratio.

An overview of efficiency results is presented in Table A.6 in the Appendix and an overall summary can be found in Tables A.27 and A.28 in the Appendix. The effect of hedging on the mean returns is negative in the in-sample analysis and positive in the out-of-sample analysis; however, it does not change positivity of the in-sample returns and negativity of the out-of-sample returns.

Performance of all hedge strategies is similar.[8] On average, they increase the out-of-sample returns by 80% and decrease the in-sample returns by 50%. The performance of the recommended simple OLS hedge ratio does not stand out and the returns stay in ten-thousandths.

Soybeans

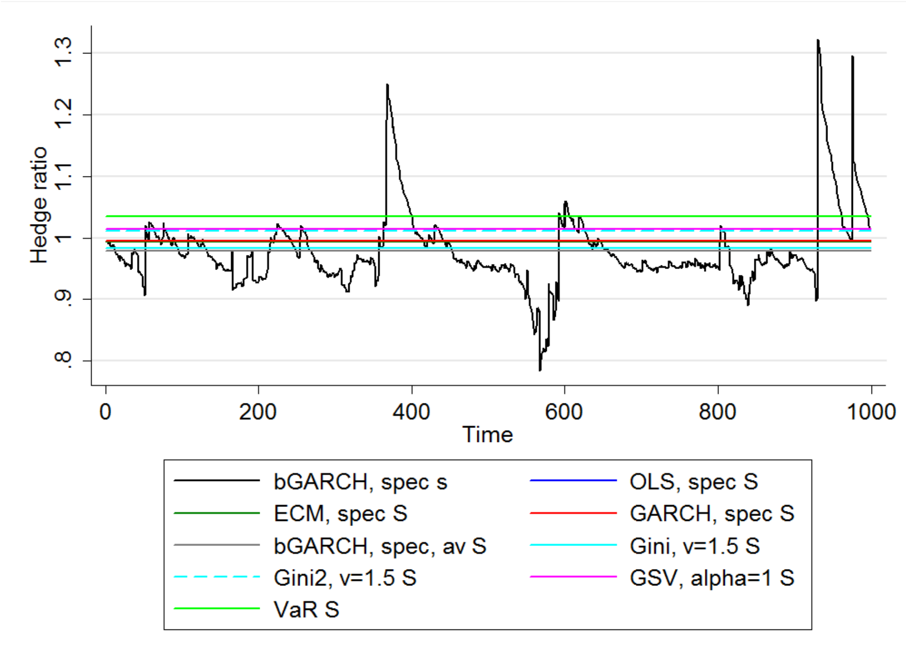
The correlation coefficient of the Soybeans' spot and futures returns is, on average, larger than 0.9, signalling a strong correlation; however, the correlation decreases with time from 0.94 to 0.88. The drop may be tracked in the out-of-sample hedge ratios. The values of Adjusted R^2 correspond to the high correlation and slowly increase with the level of model specification from 0.87 to 0.89. We suppose that the hedge ratio will be close to 1 and the variance efficiency will approach the 87% level.

Figure B.21 in the Appendix shows the values of the constant in-sample hedge ratios while Figure 5.20 depicts only the main constant hedge ratio together with the specified bivariate GARCH hedge ratio. The highest hedge ratio is provided through the VaR approach as in the cases of Platinum, Oil, and Copper and reaches the value of 1.03. In addition to the VaR hedge ratios, there are three other hedge ratios higher than one. These are the the GSV, MEG 2, and simple GARCH hedge ratios. The other hedge ratios are lower than 1 - the specified types of the OLS and ECM hedge ratios are higher than the simple ones (as in the case of Corn and Copper), but the values are close, placing around the value of 0.99. The bivariate GARCH hedge ratio is the lowest with value under 0.98 (similar pattern is observed for Oil). The specified bGARCH hedge ratio is mostly lower than the other hedge ratios, but there are three peaks approaching the value of 1.3 and one drop with value under 0.8. The fluctuation of the bGARCH hedge ratios is lower than in the case of other hedge ratios and it is comparable to the fluctuation of the Copper bGARCH hedge ratio. The bGARCH hedge ratios nearly copy each other and are highly correlated as shown in Figure B.23 in the Appendix. Hence, we assume that the results will be similar.

Looking at the out-of-sample results in Figure 5.21, the increased volatility of the bGARCH hedge ratio clearly stands out as its value reaches 2.5. The only possible reason for this extreme increase, we are able to identify, is a relatively steep drop in the correlation (decrease by 0.15 within one step). The

[8] Except for the naive hedge ratio, which is much larger than the other hedge ratios and thus leads to more extreme results.

Figure 5.20: Soybeans - overview of main in-sample HR



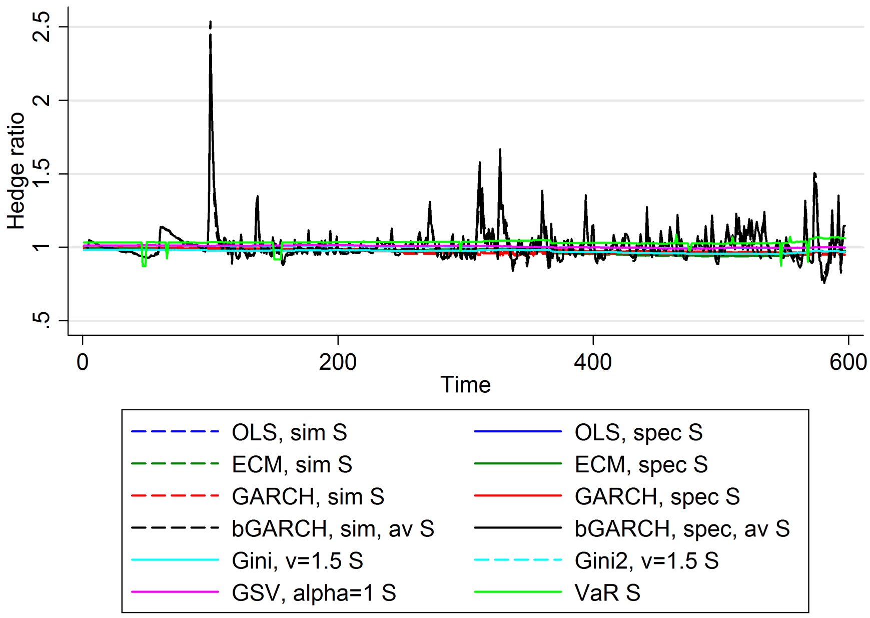
other hedge ratios seem to stay relatively constant and there is no decrease predicted based on the correlation reduction. Further, all hedge ratios except for the bGARCH hedge ratios are strongly autocorrelated.

The average values of the out-of-sample hedge ratios totally switched ranking compared to the in-sample analysis. The VaR hedge ratio is the lowest one taking the value of 0.8, whereas the bGARCH hedge ratios take the highest values of approximately 1.02 and 1.01, and they are followed by the MEG 2 and GSV hedge ratios as in the in-sample case. The simple GARCH is lower than the specified GARCH, but both of them fit to the group of econometric hedge ratios excluding the bGARCH hedge ratio. The other hedge ratios' values are close to 0.97. The described features are presented in Figure B.22 in the Appendix.

The in-sample reduction in both VaR and variance is much larger than the out-of-sample reduction, as shown in Figure 5.22. The in-sample VaR and variance reduction is comparable among the hedge strategies, as only the bGARCH hedge ratios underperform in the variance reduction. The other hedge ratios reduce the in-sample variance by 87%, which corresponds to the values of Adjusted R^2 in the econometric analysis, again. The average in-sample VaR reduction is 81%.

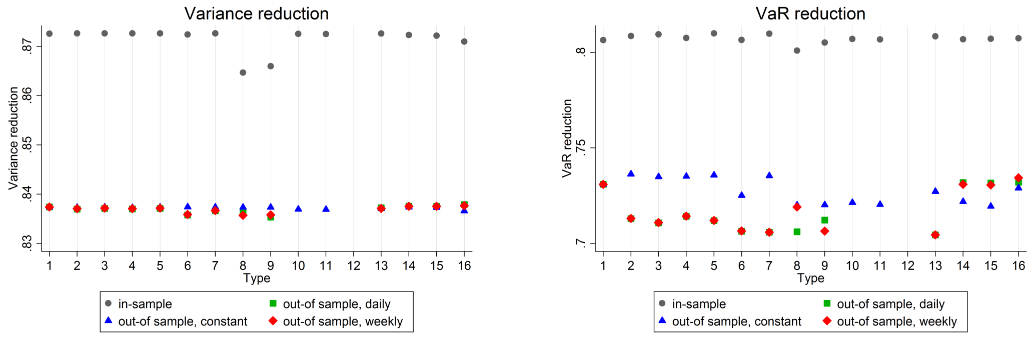
The out-of-sample performance in terms of variance is similar across the

Figure 5.21: Soybeans - overview of out-of-sample HR



hedging strategies as well, providing 83.5% variance reduction. Only the GARCH and bGARCH hedge ratios slightly underperform in the case of the daily and weekly changing hedge ratios. The VaR measure allows us to evaluate the hedge ratios better. It signals that hedging with the constant hedge ratios is more efficient than hedging with the time-varying hedge ratios, and the OLS and ECM hedge ratios outperform all other strategies in the constant hedging. Considering the time-varying hedging, the MEG 2, GSV, and VaR hedge ratios stand out. Both the above mentioned groups reduce the VaR by approximately 73.5% and they are closely followed by the naive hedge ratio, which reduces the

Figure 5.22: Soybeans - reduction in variance and VaR



VaR by 73%. The variance reduction supports the hypothesis of the constant hedge ratios while the VaR reduction does not. As the results for the OLS, ECM, MEG, GSV, and VaR hedge ratios are inconsistent for the time-varying and constant hedging, we would recommend using the simplest type of hedging - the naive hedge ratio, which has stable results.

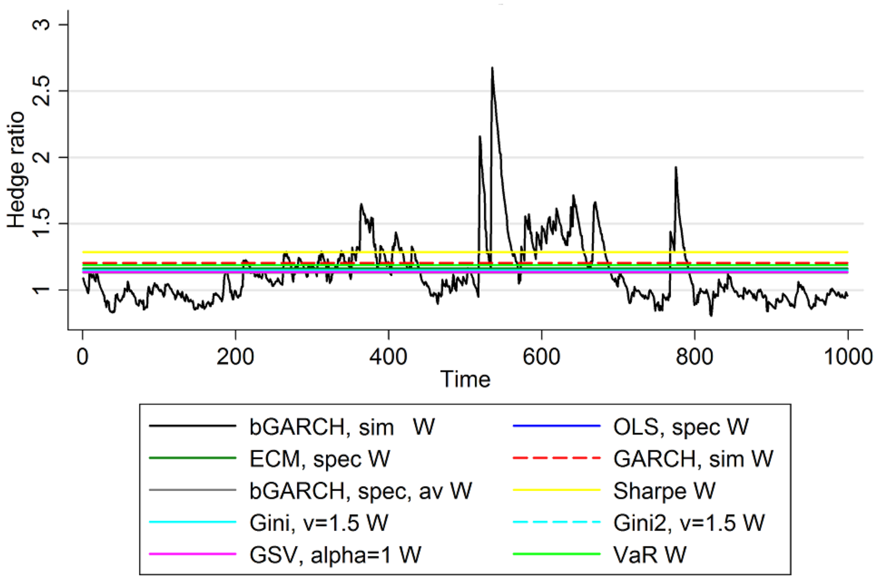
An overview of the VaR and variance reduction results can be found in Table A.7 in the Appendix and an overall summary is in Tables A.29 and A.30 in the Appendix. Soybeans is the only commodity with negative hedging effect for both the in-sample and out-of-sample returns. The best performing hedge ratios are the bGARCH hedge ratios, reducing the 0.00061 and 0.00021 returns to -0.00014 and -0.0003, only. The recommended naive hedge ratio performs worse and reduces the returns to -0.00019 and -0.00039, respectively; however, the differences are negligible and returns are still nearly zero, so we keep the recommendation.

Wheat

Correlation between the spot and futures returns is lower than in the case of the other grains, Soybeans and Corn; it begins at 0.84, then slowly decreases to 0.77 and, at the end, it jumps back to 0.82. As the differences are quite significant we may find them in the graph of the out-of-sample hedge ratios. Adjusted R^2 of all econometric models is close to 0.7, so we suppose that the in-sample variance reduction will be around 70%. Further, we know that the variance in the futures returns is much smaller than in the spot returns, which probably causes higher than 1 hedge ratios.

An overview of the constant in-sample hedge ratios can be found in Figure B.24 in the Appendix. All hedge ratios are higher than 1 as we predict in the previous paragraph. The highest is the Sharpe hedge ratio, taking the value close to 1.3, followed by the simple GARCH and VaR hedge ratios. The VaR hedge ratio belongs to the highest ones in most of the cases (Copper, Oil, Platinum, Soybeans) while the Sharpe and GARCH hedge ratios are unpredictable. The Sharpe hedge ratio is examined only for three commodities; once it is the smallest hedge ratio (Copper) and once the highest one (Oil). The GARCH hedge ratios are the highest one for Corn. Further, the specified hedge ratios are higher than the simple ones (like for Corn and Copper); the GSV and MEG hedge ratios are smaller than most of the econometric hedge ratios and MEG

Figure 5.23: Wheat - overview of main in-sample HR



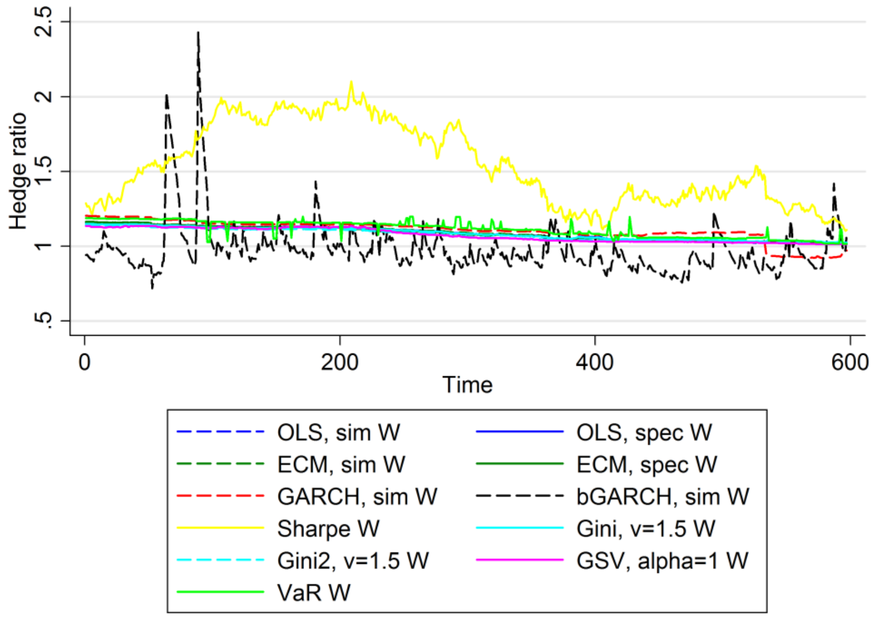
2 is smaller than MEG 1, which is unusual. The lowest hedge ratios are the average bGARCH hedge ratios (same as for Soybeans and Oil).

The time-varying simple bGARCH hedge ratio is plotted in Figure 5.23. Its amplitude is large and the hedge ratio crosses the level of 2 several times. We do not see any reason for this volatility in the middle of the sample. At the beginning and end of the sample, the hedge ratio is relatively stable with values lower than the other hedge ratios. The specified bivariate GARCH ratio encounters convergence problem for some sub-samples so we do not report its results; we try to estimate the specified bivariate GARCH at least for the in-sample data and we find that the simple and the specified hedge ratios are nearly identical with correlation coefficient of 0.999.

Examining the out-of-sample hedge ratios in Figure 5.24, we can see that the most time-varying hedge ratio is the Sharpe hedge ratio, which takes values close to 2 for approximately 100 observations. It is probable that the Sharpe hedge ratio is overestimated and its efficiency is low. The bGARCH hedge ratio is similarly volatile as in the case of the in-sample hedging, but it has two peaks at the beginning of the sample and then it fluctuates along 1. The other hedge ratios linearly decrease by roughly 0.2 which relates to the above mentioned drop in the correlation between the returns. Autocorrelation in the hedge ratios is again very strong, so a constant hedge ratio may be used.

If we compare the average out-of-sample hedge ratios with the in-sample

Figure 5.24: Wheat - overview of out-of-sample HR



hedge ratios in Figure B.25 in the Appendix, we find that the Sharpe hedge ratio increases to nearly 1.3 and the bGARCH hedge ratio decrease below 1. The rest of the hedge ratio slightly decreases but the order changes only minimally.

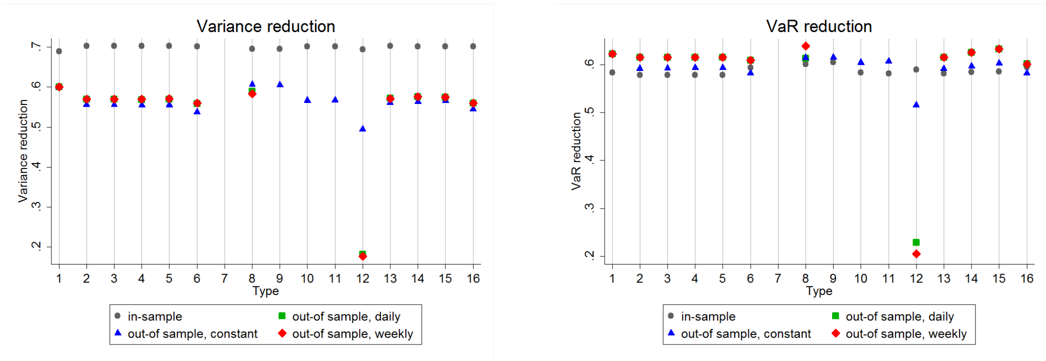
Focusing on the efficiency of the hedge ratios depicted in Figure 5.25, we can say that the in-sample variance reduction is higher than the out-of-sample reduction with values close to 70%, which corresponds to the Adjusted R^2 again. In the in-sample analysis, the performance of all hedge ratios is comparable. The Sharpe hedge ratio provides the worst results, the other results are comparable with the naive hedge ratio slightly standing out.

Disregarding the underperforming Sharpe hedge ratio, the VaR reduction results are balanced as well. Most of the hedge ratios provide results close to 60% and the bGARCH hedge ratio slightly outperforms the others in the daily-changing hedge ratio analysis.

The constant and time-varying results are close, which supports the hypothesis of constant hedge ratio. The simplest naive hedge ratio provides results comparable with the hedge ratios obtained through complex econometric estimations or calculations, so we recommend to use the naive hedge ratio.

An overview of the efficiency results can be found in Table A.8 in the Appendix and an overall summary is listed in Tables A.31 and A.32 in the Appendix. The hedging increases the mean returns in both the in-sample and

Figure 5.25: Wheat - reduction in variance and VaR



out-of-sample analyses, while the growth in the out-of-sample data is more significant and it turns negative mean returns to positive. The best performing hedge ratios are the OLS and ECM hedge ratios increasing the returns from 0.00046 and -0.00027 to 0.00068 and 0.00060, respectively. The naive hedge ratio increases the returns less to 0.00065 and 0.00048. As the returns are so close to zero, we do not suppose that it would have a significant impact on decisions of a hedging company. So we think that the naive hedge is still the best choice.

Conclusion

Overall, the reduction of variance and Value at Risk is high, proving the usefulness of hedging. Disregarding Coffee and Beef with futures returns poorly matching the spot returns and the futures thus being inappropriate for hedging, the reduction in variance takes values between 55% and 99%. The outcomes for VaR reduction are lower with values between 30% and 90%.

Despite its simplicity, the naive hedge ratio is quite successful in the risk reduction, especially considering the commodities with strongly correlated returns; on the contrary, the bivariate GARCH hedge ratio is complicated to compute and its performance does not stand over the others. The Sharpe hedge ratio is examined only for three different commodities (Copper, Oil, Wheat), but its is the worst performing hedge ratio in most of the cases, particularly in hedging with the time-varying hedge ratios. Another hedge ratio with outcomes not as good as one would expect based on the complexity of its calculation is the VaR hedge ratio, which does not outpreform even in the VaR reduction.

Our results suggest that the constant hedge ratios are as efficient as the time-varying hedge ratios in most of the cases. Further, the hedge ratios are highly correlated in time, which supports the hypothesis that time-varying hedge ratios are not necessary. We do not condemn re-estimation of hedge ratio as it may differ due to a change in correlation structure in time, but we consider daily re-estimation to be useless.

We find that the in-sample reduction of variance corresponds to Adjusted R^2 of the given econometric model. This relation arises from the definition of Adjusted R^2 - i.e. how much volatility of dependent variable is explained by the model. Using the hedge ratio resulting from the model to insure the portfolio would clearly lead to a similar reduction in the portfolio's variance. Nevertheless, the relation cannot be described by equation as the econometric model usually includes more variables contributing to the volatility explanation, so the Adjusted R^2 should be used only as an approximate measure of hedge ratio efficiency.

Our analysis shows that it is impossible to make general conclusions about the quality of individual hedge ratios. Each spot position has to be treated differently, and an analysis of the hedge ratios efficiency of each type of hedging strategy should be made before employing a specific hedge ratio. Based on our analysis we can conclude that complex hedging strategies (the bivariate GARCH or VaR hedge ratios) do not outperform simple hedging strategies such as the naive hedging or the OLS hedge ratio, so it may be convenient to use the simple methods to avoid additional costs related to re-estimation of the optimal hedge ratios.

An overview of the best performing out-of-sample hedge ratios and the recommended hedge ratios including their value and value of VaR and variance reduction can be found in Table 5.17.

Table 5.17: Best and recommended hedge ratios

	Best	Type	Δ var	HR	Best	Type	Δ VaR	HR	Recom.	Δ var	Δ VaR	HR
Beef	MEG1	day	1%	0.04	MEG2	cons.	3%	0.03	-	-	-	-
Coffee	MEG1	cons.	0%	0.00	G.,si	cons.	5%	-0.02	-	-	-	-
Copper	bG.,si	cons.	90%	0.98	GSV	week	94%	1.00	naive	90%	94%	1.00
Corn	bG.,si	week	77%	0.90	MEG1	cons.	70%	0.91	OLS,si	76%	69%	0.90
Oil	naive	-	99%	1.00	OLS,si	day	93%	1.01	naive	99%	93%	1.00
Plat.	MEG1	day	55%	0.66	MEG1	cons.	30%	0.66	OLS,sp	55%	29%	0.66
Soyb.	VaR	day	84%	0.80	OLS,si	cons.	74%	0.97	naive	84%	73%	1.00
Wheat	bG.,si	cons.	61%	0.98	bG.,si	week	64%	0.98	naive	60%	62%	1.00

5.2.3 MEG and GSV hedge ratios

We use two different methods of hedge ratio estimations: the first one (MEG 1 or Gini 1) is based on Shalit's approach and it is valid only for hedge ratios smaller than 1. The second method (MEG 2 or Gini 2) uses grid search and the standard expression for Gini coefficient and it is universal. Findings of the papers examining the MEG hedging differ and we try to re-examine some of the results. Lien and Shaffer (1999) find that the hedge ratios obtained by the two above-mentioned types of estimation differ. Lien and Luo (1993b) say that the hedge ratio decreases with the risk aversion parameter and it is close to the OLS hedge ratio for the risk parameter equal to 9. Kolb and Okunev (1992) say that the MEG hedge ratio is close to the OLS hedge ratios for small risk parameters, while it significantly differs for high risk parameter.

We use five different risk parameters for the MEG hedge ratio estimation: 1.5, 2, 5, 10, and 20, and five risk parameters for the GSV hedge ratio estimation: 1, 2, 3, 4, 5. Our target is to study the behaviour of the hedge ratios and try to make some generalizations. We are interested in the hedge ratios close to those obtained through the econometric analysis (the minimum variance hedge ratios); although the mean-variance hedge ratio is theoretically equal to the minimum variance hedge ratio under the assumption of an infinitely risk averse hedger, the hedge ratios diverge from the OLS hedge ratio with the increasing risk parameter. Therefore, we limit the risk parameters to the values listed above. The results are presented in Tables A.9 to A.16 in the Appendix.

The results for Beef and Coffee are not discussed here because they are unreliable as we show earlier. For comparison of the MEG 1 and MEG 2 estimators, we can use only the Platinum results, as the values of the other hedge ratios exceed the level of 1, and thus the MEG 1 results are unreliable. We find that both the MEG 1 and MEG 2 hedge ratios increase with the risk parameter and the MEG 1 hedge ratio covers a wider range of values. The values of the MEG 1 and MEG 2 hedge ratios generally differ, but we can say that both of them are close to the OLS hedge ratios for rather low risk parameters. Both types of MEG hedge ratios have a similar effect on the variance and VaR reduction. Essentially, low risk parameter is more efficient in the variance reduction, whilethe high risk parameter is more efficient in the VaR reduction.

The above described feature holds only for Platinum, the MEG 2 hedge ratios of the other commodities provide different results. Corn reports higher reduction of variance and VaR for high risk parameter, whereas Oil and Wheat reports most effective reduction for low risk parameter. There is not any observable pattern in the Copper and Soybeans results. Also the changes in the hedge ratios do not show out uniform dependence on the risk parameter; the MEG 2 hedge ratio increases with the risk parameter for Oil, Platinum, and Wheat, and decreases for Soybeans, Corn, and Copper. One may note that the groups of commodities in the efficiency analysis and the hedge ratio values overlap. Hence, the most general statement we can make about the MEG 2 hedge ratios is that the lower hedge ratios reduce variance and VaR more successfully, but we are unable to link any of the characteristics to the risk parameter.

The OLS hedge ratio is usually smaller than most of the MEG 2 hedge ratios, so the convergence to the hedge ratio is given by the relation between the hedge ratio value and the risk parameter. We can say that the MEG 2 hedge ratio coincides with the OLS hedge ratio for low risk parameter values in case of Platinum, for medium risk parameter values in case of Oil and Wheat, and for high risk parameter values for Copper, Corn, and Soybeans. However, the risk parameters we use are small compared to the risk parameters used by Lien and Luo (1993b) and Kolb and Okunev (1992), who use risk parameters as high as 200. In such measure, we could conclude that the MEG 2 hedge ratios match the OLS hedge ratios for low values of risk parameter.

Disregarding Wheat results,[9] the GSV hedge ratio is lowest for the risk parameter equal to 5, but the hedge ratio does not always gradually decrease with the risk parameter as for Copper, Corn, and Soybeans. In some cases, it gradually increases with the risk parameter and then it starts to decrease or even sharply drops (e.g. for Oil and Platinum). In most of the cases, the GSV hedge ratio provides better variance and VaR reduction for low values of the risk parameter, the exception is Platinum, again. Although the results for the GSV hedge ratio are more uniform, we cannot make general statements, as there are some exceptions with opposite results.

The MEG 2 and GSV results confirm that it is impossible to generalize the effect of individual parameters as it has a different impact on different commodities.

[9]Hedge ratio increases with the risk parameter for Wheat.

Chapter 6

Conclusion

Hedging is an effective instrument for lowering the risk resulting from volatility in spot commodity prices; the risk is reduced by taking an opposite position on futures market. As spot and futures returns correlate, loss on spot market is offset by gain on futures market and vice versa. Even though hedging is widely examined in the theoretical literature, not all companies use it in practice. However, with increasing volatility of commodity prices, it becomes more and more important.[10]

A hedging company faces several problems: it has to choose futures for hedging and determine the ratio between spot and futures units. This ratio is called hedge ratio. The main criterion for futures selection is correlation of its returns with spot returns; the hedging efficiency increases with the correlation. If the match between futures and spot returns is poor, there is virtually no risk reduction at all. The optimal hedging ratio is a subject of many financial papers and there is a wide variety of approaches suggested for hedge ratio estimation.

Our thesis provides a complex theoretical overview of hedge ratio types, discusses their implementation into practice and examines efficiency of individual hedge ratios using eight different commodities. As far as we know, this is the first comprehensive study of so many types of hedge ratios applied to higher number of commodities; hence, it is a valuable addition to the existing literature. Further, the detailed description of hedge ratios' implementation and evaluation can be used by actual companies as instructions for identification of the most appropriate hedging strategy.

Specifically, we examine the following hedge ratios: naive, minimum vari-

[10]We illustrate the problem of increasing volatility on Standard & Poor Goldman Sachs Commodity Index, whose annual volatility increased from 13 percent in 1981 to 23 percent in 2011.

ance, Sharpe, mean extended Gini coefficient, generalized semivariance, and Value at Risk hedge ratios. Most of the hedge ratios are obtained through calculation or grid search, while the minimum variance hedge ratio estimation employs an econometric analysis. There are several econometric models suitable for the estimation and we study all of them, i.e. OLS, error correction model, GARCH and bivariate GARCH models.

We apply the hedge ratio on daily data of eight commodities: Beef, Coffee, Copper, Corn, Oil, Platinum, Soybeans, and Wheat. The data cover period from May 1, 2007 to August 31, 2013 and contain approximately 1600 observations. The data sample is divided into in-sample and out-of-sample parts, where the former is used for analysis and simulation of real hedging, and a hedge ratios evaluation is then performed on the latter one. We consider three different levels of time variance - constant hedge ratio, weekly changing hedge ratio and daily changing hedge ratio. The constant hedge ratio applies the hedge ratios estimated using the in-sample data on the out-of-sample data, the daily changing hedge ratio employs rolling window of the last 1000 observations to estimate the hedge ratio for "tomorrow", and the week hedge ratio uses averages of last-week's daily hedge ratio for determination of the hedge ratio for the next week.[11]

The efficiency of the hedge ratio types is measured through reduction in variance and Value at Risk of hedged portfolio compared to the unhedged portfolio.

The hedge ratios' value and the efficiency of individual hedge ratios depend on correlation structure of spot and futures returns of given commodity and it is impossible to generalize the results. Let us briefly discuss the results for individual commodities.

Beef and Coffee face a problem of poor correlation between spot and futures return, so the risk reduction is close to none.

The most successful hedge ratio in terms of the variance reduction for Copper is the specified bivariate GARCH hedge ratio, but it underperforms in terms of the VaR reduction. The most stable results regarding the two types of efficiency are provided by the naive hedge with the out-of-sample VaR reduction of 95% and the out-of-sample variance reduction of 90%. All Copper hedge ratios lie in interval 0.95 to 1.

Corn efficiency results are significantly different for the VaR and variance

[11] Ad the daily hedge ratio: At time t, observations $(t - 1000)$ to t are used for estimation of hedge ratio in $t + 1$.

reductions; the most stable results are obtained through the MEG 1 hedge ratio, as it has above-average results for the variance reduction (76%) and average results for the VaR reduction (70%) considering the out-of-sample part. The Corn hedge ratios are divided into two groups, one takes values of about 1.02, the other hedge ratios are much lower with the values close to 0.9.

Oil hedging is the most efficient one with 98% of the variance reduction and 93% of the VaR reduction. Performance for all hedge ratios except for the bGARCH and Sharpe hedge ratios is comparable. The named hedge ratios underperform and take the most extreme values, 0.95 and 1.15, respectively. The other hedge ratio values accumulate along unity.

Worse performance of Platinum hedging relates to the lower correlation between returns, the VaR reduction is only 30% and the variance reduction takes value of approximately 55%. The variance efficiency is balanced across the hedge ratios, with only the bGARCH and naive hedge ratios underperforming. The MEG 1 hedge ratio slightly stands out in the VaR efficiency, but the results of all hedge ratios except for the bGARCH and naive are comparable. The Platinum hedge ratios are lower than others with values between 0.65 and 0.7.

Soybeans hedging has the average efficiency; the variance reduction is nearly 84% and the VaR reduction is 73%. The results for the variance reduction are very similar, while the VaR efficiency significantly differs not only for individual hedge ratios but also for the the types of hedging (i.e. constant vs time varying). Considering the time varying hedging, the best results are provided by the MEG 2, GSV, and VaR hedge ratios. On the other, the OLS and ECM hedge ratios stand out in the constant hedging. The naive hedge ratio performs good as well. Regarding the hedge ratio values, we can divide the hedge ratios into two groups: bGARCH, VaR, GSV, and MEG 2 are slightly higher than 1, and the other hedge ratios take values close to 0.98.

The performance of Wheat hedging is rather subnormal; VaR and variance are reduced by approximately 60%. Results of individual hedge ratios are relatively close, only the Sharpe hedge ratio significantly underperforms. The naive and simple bGARCH hedge ratios are slightly better than the others. Most of the hedge ratios' values are close to 1.1.

We confirm that the value of Adjusted R^2 of used econometric models corresponds to the in-sample volume variance reduction as it is indicated by the definition of Adjusted R^2. Although, Adjusted R^2 is influenced by all dependent variables and the real in-sample reduction is thus usually smaller than the value of Adjusted R^2.

There are only two generalizations resulting from our analysis, and they refer to the performance of the naive and OLS hedge ratios and the constant vs time varying type of hedging. The more complex hedge ratios, such as the bGARCH or VaR hedge ratios, do not significantly outperform the simple naive and OLS hedge ratios. Moreover, the naive and OLS hedge ratios provide more stable results and one of them always ranks among the best performing hedge ratios. Good results of the naive hedge ratio are conditioned by strong correlation of returns. Considering the usage simplicity of these two types of hedge ratios, some companies may favour them.

The constant hedge ratios mostly provide just as good efficiency result as the time-varying hedge ratios, so the daily re-estimation of hedge ratios does not pay off. Nevertheless, it is appropriate to periodically check the hedge ratio values to detect possible significant changes in time and thus avoid losses.

Based on the analysis, we advise commodities hedgers to remember the following principle. The performance of all types of hedge ratios is individual for each commodity and depends on correlation structure of returns and price developments; hence, every hedging issue should be considered separately. We recommend performance evaluation of the hedge ratios using historical data and then choosing the optimal type of hedge ratio based on comparison of risk reduction and costs related to calculation/estimation. Our thesis can be used as a guide for implementation and performance evaluation of the above mentioned hedge ratios. Even though we use futures traded on American exchanges, European companies may use futures traded on European commodities exchanges (e.g. EEX for energy, LME for metals), which better reflect the movement in European spot prices.

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Appendix A

Tables

Table A.1: Beef - variance and VaR reduction

Beef	in-sample		out-of sample, day		out-of sample, const.		out-of sample, week	
	%Δ var	%Δ VaR	%Δ var	%Δ VaR	%Δ var	%Δ VaR	%Δ var	%Δ VaR
Naive	-214.87%	-89.691%	-193.93%	-76.055%	-193.93%	-76.055%	-193.93%	-76.055%
OLS,si	0.437%	-1.698%	0.408%	1.253%	0.509%	1.361%	0.457%	1.275%
OLS,sp	0.407%	-1.233%	0.407%	0.189%	0.511%	0.161%	0.445%	0.194%
ECM,si	0.433%	-1.408%	0.412%	0.863%	0.516%	0.892%	0.459%	0.879%
ECM,sp	0.374%	-2.173%	0.425%	-0.106%	0.493%	-0.235%	0.460%	-0.107%
GARCH,si	0.435%	-1.611%	0.443%	1.939%	0.499%	1.717%	0.490%	1.964%
GARCH,sp	-	-	-	-	-	-	-	-
bGARCH,si	0.305%	-1.178%	0.425%	1.555%	0.498%	1.727%	0.490%	1.625%
bGARCH,sp	0.364%	-0.583%	0.489%	0.435%	0.513%	1.178%	0.500%	0.552%
bGARCH,si,a	0.434%	-1.513%	-	-	0.515%	0.995%	-	-
bGARCH,sp,a	0.390%	-1.702%	-	-	0.502%	-0.059%	-	-
Sharpe	-	-	-	-	-	-	-	-
Gini, v=1.5	0.437%	-1.691%	0.583%	1.254%	0.510%	1.330%	0.516%	1.175%
Gini2, v=1.5	0.404%	-0.133%	0.500%	2.170%	0.449%	2.517%	0.450%	2.120%
GSV, α=1	0.437%	-1.713%	0.399%	0.600%	0.507%	1.437%	0.354%	0.527%
VaR	0.436%	-1.712%	0.448%	1.512%	0.504%	1.553%	0.454%	1.862%

Table A.2: Coffee - variance and VaR reduction

Coffee	in-sample		out-of sample, day		out-of sample, const.		out-of sample, week	
	%Δ var	%Δ VaR	%Δ var	%Δ VaR	%Δ var	%Δ VaR	%Δ var	%Δ VaR
Naive	-182.09%	-84.887%	-165.37%	-49.774%	-165.37%	-49.774%	-165.37%	-49.774%
OLS,si	0.002%	-0.254%	-0.258%	0.690%	0.037%	0.005%	-0.164%	0.806%
OLS,sp	-0.138%	-2.478%	-0.327%	0.409%	-0.385%	0.009%	-0.301%	0.460%
ECM,si	-	-	-	-	-	-	-	-
ECM,sp	-	-	-	-	-	-	-	-
GARCH,si	-0.549%	-5.146%	-0.447%	0.146%	0.171%	4.675%	-0.381%	0.306%
GARCH,sp	-0.230%	-3.362%	-0.106%	0.690%	-0.550%	-0.730%	-0.078%	0.791%
bGARCH,si	0.004%	-0.642%	0.141%	0.780%	0.087%	0.425%	0.117%	0.834%
bGARCH,sp	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	-	-
bGARCH,si,a	-0.002%	-0.381%	-	-	0.086%	0.422%	-	-
bGARCH,sp,a	-	-	-	-	-	-	-	-
Sharpe	-	-	-	-	-	-	-	-
Gini, v=1.5	-0.117%	-2.584%	0.010%	0.051%	0.215%	2.365%	-0.076%	0.012%
Gini2, v=1.5	0.002%	-0.180%	-0.029%	1.035%	0.027%	-0.042%	-0.099%	0.996%
GSV, α=1	-0.091%	-1.923%	-0.426%	-1.359%	0.205%	1.993%	-0.491%	-1.207%
VaR	0.000%	-0.028%	0.141%	1.242%	0.004%	-0.006%	0.188%	0.591%

Table A.3: Copper - variance and VaR reduction

Copper	in-sample		out-of sample, day		out-of sample, const.		out-of sample, week	
	%Δ var	%Δ VaR	%Δ var	%Δ VaR	%Δ var	%Δ VaR	%Δ var	%Δ VaR
Naive	91.788%	90.224%	90.337%	94.391%	90.337%	94.391%	90.339%	94.391%
OLS,si	91.876%	90.066%	90.254%	93.718%	90.463%	93.453%	90.258%	93.717%
OLS,sp	91.874%	90.394%	90.279%	93.872%	90.457%	93.830%	90.284%	93.870%
ECM,si	91.874%	90.423%	90.293%	93.952%	90.455%	93.896%	90.298%	93.941%
ECM,sp	91.870%	90.507%	90.304%	94.107%	90.448%	94.133%	90.309%	94.124%
GARCH,si	-	-	-	-	-	-	-	-
GARCH,sp	-	-	-	-	-	-	-	-
bGARCH,si	92.117%	87.866%	90.102%	90.519%	90.454%	92.454%	90.128%	91.537%
bGARCH,sp	92.439%	89.328%	90.399%	92.653%	90.467%	93.082%	90.426%	92.230%
bGARCH,si,a	91.872%	89.549%	-	-	90.467%	93.078%	-	-
bGARCH,sp,a	91.861%	90.643%	-	-	90.433%	94.267%	-	-
Sharpe	90.343%	79.843%	86.471%	77.268%	89.087%	82.099%	86.781%	76.880%
Gini, v=1.5	91.875%	89.944%	90.288%	93.648%	90.465%	93.291%	90.289%	93.598%
Gini2, v=1.5	91.795%	90.410%	90.332%	94.417%	90.347%	94.312%	90.334%	94.417%
GSV, α=1	91.788%	90.224%	90.330%	94.458%	90.339%	94.391%	90.332%	94.459%
VaR	91.787%	90.199%	90.328%	94.288%	90.338%	94.402%	90.330%	94.281%

Table A.4: Corn - variance and VaR reduction

Corn	in-sample		out-of sample, day		out-of sample, const.		out-of sample, week	
	%Δ var	%Δ VaR	%Δ var	%Δ VaR	%Δ var	%Δ VaR	%Δ var	%Δ VaR
Naive	75.444%	72.584%	74.708%	65.797%	74.708%	65.797%	74.708%	65.797%
OLS,si	75.520%	72.975%	75.623%	69.675%	75.469%	66.736%	75.688%	69.651%
OLS,sp	75.519%	72.935%	75.542%	69.073%	75.387%	66.521%	75.598%	69.070%
ECM,si	75.520%	72.963%	75.620%	69.728%	75.444%	66.670%	75.685%	69.708%
ECM,sp	75.514%	72.883%	75.500%	69.650%	75.278%	66.282%	75.548%	69.618%
GARCH,si	74.427%	77.734%	73.319%	65.410%	71.576%	64.215%	73.277%	65.425%
GARCH,sp	74.477%	77.619%	73.146%	65.698%	71.698%	64.237%	73.055%	65.429%
bGARCH,si	74.324%	72.667%	74.712%	64.446%	75.583%	67.051%	76.795%	64.427%
bGARCH,sp	74.924%	72.365%	75.195%	64.631%	76.276%	69.363%	76.583%	64.592%
bGARCH,si,a	75.507%	72.384%	-	-	75.723%	67.464%	-	-
bGARCH,sp,a	75.516%	72.894%	-	-	75.302%	66.304%	-	-
Sharpe	-	-	-	-	-	-	-	-
Gini, v=1.5	75.518%	72.880%	75.927%	69.891%	75.578%	67.038%	75.869%	69.825%
Gini2, v=1.5	75.057%	74.886%	73.878%	66.355%	73.251%	65.216%	73.861%	66.348%
GSV, α=1	74.969%	75.234%	73.504%	66.156%	72.991%	65.425%	73.500%	66.154%
VaR	75.154%	74.405%	73.427%	64.498%	73.555%	65.121%	73.643%	64.484%

Table A.5: Oil - variance and VaR reduction

Oil	in-sample		out-of sample, day		out-of sample, const.		out-of sample, week	
	%Δ var	%Δ VaR	%Δ var	%Δ VaR	%Δ var	%Δ VaR	%Δ var	%Δ VaR
Naive	82.838%	83.118%	98.722%	92.718%	98.722%	92.718%	98.722%	92.718%
OLS,si	82.857%	83.308%	98.682%	92.853%	98.676%	92.822%	98.683%	92.853%
OLS,sp	-	-	-	-	-	-	-	-
ECM,si	82.844%	82.748%	98.636%	92.853%	98.605%	92.619%	98.636%	92.852%
ECM,sp	-	-	-	-	-	-	-	-
GARCH,si	82.845%	82.989%	98.715%	92.720%	98.717%	92.733%	98.715%	92.719%
GARCH,sp	82.846%	82.962%	98.712%	92.729%	98.715%	92.737%	98.712%	92.728%
bGARCH,si	82.826%	83.268%	98.332%	88.389%	98.726%	92.697%	98.412%	88.687%
bGARCH,sp	82.821%	83.333%	98.335%	88.857%	98.727%	92.691%	98.422%	89.059%
bGARCH,si,a	80.312%	81.107%	-	-	98.727%	92.517%	-	-
bGARCH,sp,a	81.773%	82.477%	-	-	98.616%	92.679%	-	-
Sharpe	82.807%	82.851%	94.792%	81.389%	98.503%	91.878%	94.751%	80.784%
Gini, v=1.5	82.844%	82.746%	98.636%	92.762%	98.605%	92.622%	98.633%	92.758%
Gini2, v=1.5	82.856%	83.228%	98.700%	92.762%	98.691%	92.773%	98.699%	92.760%
GSV, α=1	82.851%	82.940%	98.711%	92.765%	98.706%	92.760%	98.710%	92.766%
VaR	82.211%	82.094%	97.783%	88.334%	97.468%	88.477%	97.796%	89.097%

Table A.6: Platinum - variance and VaR reduction

Platinum	in-sample		out-of sample, day		out-of sample, const.		out-of sample, week	
	%Δ var	%Δ VaR	%Δ var	%Δ VaR	%Δ var	%Δ VaR	%Δ var	%Δ VaR
Naive	43.410%	30.865%	38.736%	26.983%	38.736%	26.983%	38.736%	26.983%
OLS,si	53.451%	38.285%	54.455%	29.330%	54.269%	29.744%	54.501%	29.360%
OLS,sp	53.393%	38.552%	54.611%	29.125%	54.483%	29.625%	54.639%	29.118%
ECM,si	53.450%	38.469%	54.410%	29.472%	54.253%	29.800%	54.442%	29.500%
ECM,sp	53.426%	38.513%	54.584%	29.474%	54.423%	29.086%	54.608%	29.490%
GARCH,si	53.445%	37.326%	54.236%	29.809%	54.351%	29.418%	54.288%	29.796%
GARCH,sp	53.428%	38.506%	54.466%	29.421%	54.419%	29.096%	54.506%	29.450%
bGARCH,si	51.513%	33.863%	53.457%	27.007%	54.265%	29.759%	54.482%	28.857%
bGARCH,sp	51.720%	35.438%	53.575%	28.418%	54.186%	29.873%	54.627%	27.851%
bGARCH,si,a	53.448%	38.470%	-	-	54.211%	29.888%	-	-
bGARCH,sp,a	53.449%	38.470%	-	-	54.218%	29.893%	-	-
Sharpe	-	-	-	-	-	-	-	-
Gini, v=1.5	53.405%	38.290%	54.644%	30.451%	54.465%	29.330%	54.613%	30.441%
Gini2, v=1.5	53.450%	37.503%	54.551%	29.428%	54.306%	29.603%	54.522%	29.426%
GSV, α=1	53.450%	38.028%	54.524%	29.196%	54.281%	29.698%	54.480%	29.180%
VaR	53.343%	37.776%	54.244%	29.764%	53.757%	30.381%	54.291%	29.778%

Table A.7: Soybeans - variance and VaR reduction

Soybeans	in-sample		out-of sample, day		out-of sample, const.		out-of sample, week	
	%Δ var	%Δ VaR	%Δ var	%Δ VaR	%Δ var	%Δ VaR	%Δ var	%Δ VaR
Naive	87.262%	80.636%	83.743%	73.095%	83.743%	73.095%	83.743%	73.095%
OLS,si	87.269%	80.853%	83.699%	71.301%	83.731%	73.631%	83.707%	71.312%
OLS,sp	87.267%	80.937%	83.711%	71.080%	83.738%	73.491%	83.719%	71.094%
ECM,si	87.269%	80.753%	83.702%	71.424%	83.729%	73.514%	83.709%	71.431%
ECM,sp	87.268%	80.996%	83.712%	71.195%	83.737%	73.577%	83.720%	71.205%
GARCH,si	87.246%	80.648%	83.579%	70.637%	83.742%	72.513%	83.588%	70.655%
GARCH,sp	87.268%	80.977%	83.664%	70.592%	83.737%	73.541%	83.670%	70.592%
bGARCH,si	86.472%	80.094%	83.621%	70.613%	83.735%	72.011%	83.571%	71.913%
bGARCH,sp	86.602%	80.512%	83.535%	71.220%	83.735%	72.019%	83.583%	70.650%
bGARCH,si,a	87.256%	80.699%	-	-	83.695%	72.142%	-	-
bGARCH,sp,a	87.254%	80.674%	-	-	83.692%	72.041%	-	-
Sharpe	-	-	-	-	-	-	-	-
Gini, v=1.5	87.264%	80.840%	83.726%	70.453%	83.712%	72.720%	83.711%	70.449%
Gini2, v=1.5	87.233%	80.681%	83.757%	73.187%	83.738%	72.191%	83.754%	73.092%
GSV, α=1	87.221%	80.707%	83.756%	73.164%	83.733%	71.944%	83.754%	73.061%
VaR	87.101%	80.732%	83.792%	73.205%	83.661%	72.902%	83.768%	73.441%

Table A.8: Wheat - variance and VaR reduction

Wheat	in-sample		out-of sample, day		out-of sample, const.		out-of sample, week	
	%Δ var	%Δ VaR	%Δ var	%Δ VaR	%Δ var	%Δ VaR	%Δ var	%Δ VaR
Naive	68.865%	58.379%	60.015%	62.217%	60.015%	62.217%	60.015%	62.217%
OLS,si	70.208%	57.790%	56.931%	61.543%	55.612%	59.168%	56.979%	61.545%
OLS,sp	70.208%	57.810%	56.900%	61.521%	55.549%	59.267%	56.946%	61.524%
ECM,si	70.207%	57.849%	56.871%	61.540%	55.487%	59.363%	56.919%	61.543%
ECM,sp	70.207%	57.837%	56.974%	61.535%	55.506%	59.334%	57.022%	61.537%
GARCH,si	70.108%	59.338%	55.909%	60.858%	53.741%	58.220%	55.980%	60.899%
GARCH,sp	-	-	-	-	-	-	-	-
bGARCH,si	69.469%	60.064%	58.953%	61.290%	60.569%	61.429%	58.255%	63.841%
bGARCH,sp	69.501%	60.502%	-	-	60.525%	61.464%	-	-
bGARCH,si,a	70.171%	58.371%	-	-	56.606%	60.405%	-	-
bGARCH,sp,a	-	-	-	-	-	-	-	-
Sharpe	-69.372%	-58.922%	-18.117%	-22.894%	-49.400%	-51.474%	17.704%	20.519%
Gini, v=1.5	70.202%	58.121%	57.158%	61.523%	56.028%	59.154%	57.142%	61.523%
Gini2, v=1.5	70.189%	58.469%	57.539%	62.515%	56.332%	59.652%	57.531%	62.557%
GSV, α=1	70.175%	58.492%	57.442%	63.258%	56.561%	60.240%	57.421%	63.258%
VaR	70.169%	59.413%	55.973%	60.210%	54.480%	58.215%	55.935%	60.095%

Table A.9: Beef - MEG and GSV hedge ratios

Beef			in		out, daily		out, constant		out, weekly	
	HR in	HR out	%Δ var	%Δ VaR	%Δ var	%Δ VaR	%Δ var	%Δ VaR	%Δ var	%Δ VaR
Gini, v=1.5	0.043	0.043	-0.4%	1.7%	-0.6%	-1.3%	-0.5%	-1.3%	-1.5%	0.9%
Gini, v=2	0.042	0.043	-0.4%	1.7%	-0.6%	-1.4%	-0.5%	-1.4%	-1.4%	0.9%
Gini, v=5	0.042	0.043	-0.4%	1.7%	-0.5%	-1.7%	-0.5%	-1.4%	-1.4%	0.9%
Gini, v=10	0.041	0.043	-0.4%	1.7%	-0.5%	-1.7%	-0.5%	-1.6%	-1.5%	0.9%
Gini, v=20	0.034	0.039	-0.4%	0.7%	-0.4%	-2.3%	-0.5%	-2.3%	-1.4%	0.5%
Gini2, v=1.5	0.031	0.035	-0.4%	0.1%	-0.5%	-2.2%	-0.4%	-2.5%	-1.2%	0.4%
Gini2, v=2	0.030	0.034	-0.4%	-0.1%	-0.5%	-2.3%	-0.4%	-2.3%	-1.2%	0.3%
Gini2, v=5	0.035	0.040	-0.4%	0.8%	-0.5%	-2.0%	-0.5%	-2.3%	-1.4%	0.4%
Gini2, v=10	0.041	0.044	-0.4%	1.7%	-0.6%	-1.7%	-0.5%	-1.6%	-1.5%	0.5%
Gini2, v=20	0.054	0.051	-0.4%	1.2%	-0.6%	-0.8%	-0.5%	-0.2%	-1.8%	0.9%
GSV, α=1	0.042	0.036	-0.4%	1.7%	-0.4%	-0.6%	-0.5%	-1.4%	-1.3%	1.0%
GSV, α=2	0.059	0.054	-0.4%	2.1%	-0.4%	0.5%	-0.5%	0.2%	-1.9%	1.3%
GSV, α=3	0.077	0.069	-0.2%	1.5%	-0.4%	-0.5%	-0.4%	-1.4%	-2.3%	-0.3%
GSV, α=4	0.094	0.092	0.2%	1.0%	-0.2%	-1.9%	-0.1%	-1.4%	-2.7%	-1.0%
GSV, α=5	0.107	0.117	0.5%	-0.5%	0.2%	-0.6%	0.2%	-0.6%	-3.0%	-1.3%
OLS, simple	0.043	0.043								

Table A.10: Coffee - MEG and GSV hedge ratios

Coffee			in		out, daily		out, constant		out, weekly	
	HR in	HR out	%Δ var	%Δ VaR	%Δ var	%Δ VaR	%Δ var	%Δ VaR	%Δ var	%Δ VaR
Gini, ν=1.5	-0.029	-0.002	0.1%	2.6%	0.0%	-0.1%	-0.2%	-2.4%	0.5%	1.6%
Gini, ν=2	-0.028	-0.005	0.1%	2.3%	-0.1%	-0.2%	-0.2%	-2.2%	0.8%	1.5%
Gini, ν=5	-0.001	0.011	0.0%	0.1%	-0.1%	-1.3%	0.0%	0.0%	-2.7%	-0.5%
Gini, ν=10	0.019	0.025	0.1%	2.3%	0.1%	-1.9%	0.3%	0.3%	-5.5%	-1.9%
Gini, ν=20	0.033	0.030	0.2%	3.5%	0.2%	-1.5%	0.6%	0.8%	-6.3%	-2.2%
Gini2, ν=1.5	-0.002	0.013	0.0%	0.2%	0.0%	-1.0%	0.0%	0.0%	-3.1%	-0.2%
Gini2, ν=2	-0.002	0.013	0.0%	0.2%	0.0%	-1.0%	0.0%	0.0%	-3.1%	-0.2%
Gini2, ν=5	0.016	0.018	0.1%	2.0%	-0.1%	-2.1%	0.2%	0.1%	-4.6%	-1.2%
Gini2, ν=10	0.032	0.018	0.2%	3.3%	-0.4%	-2.5%	0.5%	0.7%	-5.4%	-1.9%
Gini2, ν=20	0.045	0.024	0.4%	3.8%	-0.3%	-2.7%	0.8%	1.9%	-6.6%	-3.5%
GSV, α=1	-0.026	0.017	0.1%	1.9%	0.4%	1.4%	-0.2%	-2.0%	-3.2%	-0.1%
GSV, α=2	-0.002	0.013	0.0%	0.2%	0.0%	-1.6%	0.0%	0.0%	-3.2%	-0.2%
GSV, α=3	-0.027	-0.003	0.1%	2.1%	-0.1%	-0.1%	-0.2%	-2.1%	0.4%	1.7%
GSV, α=4	-0.096	-0.045	1.5%	7.2%	0.3%	-1.4%	0.3%	-3.9%	10.8%	6.3%
GSV, α=5	-0.100	-0.086	1.7%	7.5%	0.4%	-3.5%	0.3%	-3.9%	19.5%	7.3%
OLS, simple	-0.003	0.012								

Table A.11: Copper - MEG and GSV hedge ratios

Copper			in		out, daily		out, constant		out, weekly	
	HR in	HR out	%Δ var	%Δ VaR	%Δ var	%Δ VaR	%Δ var	%Δ VaR	%Δ var	%Δ VaR
Gini, ν=1.5	0.968	0.983	-91.9%	-89.9%	-90.3%	-93.6%	-90.5%	-93.3%	-99.4%	-94.8%
Gini, ν=2	0.972	0.983	-91.9%	-90.2%	-90.3%	-93.8%	-90.5%	-93.7%	-99.4%	-94.9%
Gini, ν=5	0.979	0.983	-91.9%	-90.5%	-90.3%	-94.1%	-90.4%	-94.3%	-99.4%	-94.9%
Gini, ν=10	0.980	0.986	-91.9%	-90.6%	-90.3%	-94.1%	-90.4%	-94.4%	-99.4%	-94.6%
Gini, ν=20	0.980	0.990	-91.9%	-90.6%	-90.2%	-94.2%	-90.4%	-94.4%	-99.4%	-94.3%
Gini2, ν=1.5	0.999	1.000	-91.8%	-90.4%	-90.3%	-94.4%	-90.3%	-94.3%	-99.4%	-95.4%
Gini2, ν=2	0.999	1.000	-91.8%	-90.3%	-90.3%	-94.4%	-90.3%	-94.3%	-99.4%	-95.4%
Gini2, ν=5	1.000	1.000	-91.8%	-90.3%	-90.3%	-94.5%	-90.3%	-94.4%	-99.4%	-95.4%
Gini2, ν=10	0.998	1.000	-91.8%	-90.5%	-90.3%	-94.5%	-90.4%	-94.2%	-99.4%	-95.4%
Gini2, ν=20	0.990	0.998	-91.8%	-90.4%	-90.3%	-94.5%	-90.4%	-94.2%	-99.4%	-95.4%
GSV, α=1	1.000	1.000	-91.8%	-90.2%	-90.3%	-94.5%	-90.3%	-94.4%	-99.4%	-95.4%
GSV, α=2	0.959	0.987	-91.9%	-89.5%	-90.2%	-93.1%	-90.5%	-93.1%	-99.3%	-94.4%
GSV, α=3	0.820	0.940	-89.7%	-77.5%	-88.2%	-81.8%	-88.4%	-79.6%	-97.5%	-84.5%
GSV, α=4	0.732	0.923	-86.3%	-67.1%	-85.7%	-73.9%	-85.2%	-71.2%	-95.0%	-79.7%
GSV, α=5	0.688	0.985	-84.1%	-62.1%	-83.7%	-69.4%	-83.1%	-66.4%	-93.2%	-76.2%
OLS, simple	0.970	0.986								

Table A.12: Corn - MEG and GSV hedge ratios

Corn			in		out, daily		out, constant		out, weekly	
	HR in	HR out	%Δ var	%Δ VaR	%Δ var	%Δ VaR	%Δ var	%Δ VaR	%Δ var	%Δ VaR
Gini, ν=1.5	0.964	0.906	-75.5%	-72.9%	-75.9%	-69.9%	-75.6%	-67.0%	-91.6%	-78.0%
Gini, ν=2	0.970	0.915	-75.5%	-73.0%	-75.9%	-70.1%	-75.4%	-66.7%	-91.7%	-78.1%
Gini, ν=5	0.977	0.923	-75.5%	-72.9%	-75.7%	-69.5%	-75.3%	-66.3%	-91.6%	-78.2%
Gini, ν=10	0.980	0.916	-75.5%	-72.9%	-75.7%	-69.5%	-75.2%	-66.2%	-91.4%	-78.2%
Gini, ν=20	0.986	0.897	-75.5%	-72.8%	-75.6%	-68.8%	-75.1%	-66.1%	-91.1%	-74.6%
Gini2, ν=1.5	1.045	1.014	-75.1%	-74.9%	-73.9%	-66.4%	-73.3%	-65.2%	-90.7%	-76.5%
Gini2, ν=2	1.050	1.018	-75.0%	-75.0%	-73.7%	-66.3%	-73.1%	-65.4%	-90.6%	-76.1%
Gini2, ν=5	1.054	1.014	-74.9%	-75.5%	-73.7%	-66.4%	-72.9%	-65.5%	-90.5%	-76.3%
Gini2, ν=10	1.051	0.996	-75.0%	-75.1%	-74.0%	-66.9%	-73.0%	-65.4%	-90.7%	-76.5%
Gini2, ν=20	1.031	0.941	-75.2%	-74.0%	-74.7%	-69.3%	-73.8%	-65.2%	-91.0%	-78.4%
GSV, α=1	1.052	1.025	-75.0%	-75.2%	-73.5%	-66.2%	-73.0%	-65.4%	-90.4%	-75.3%
GSV, α=2	0.979	0.900	-75.5%	-72.9%	-75.5%	-68.8%	-75.2%	-66.2%	-91.2%	-75.4%
GSV, α=3	0.803	0.706	-73.3%	-62.4%	-73.4%	-60.0%	-76.2%	-64.8%	-86.9%	-72.3%
GSV, α=4	0.700	0.605	-69.7%	-56.2%	-69.5%	-53.1%	-73.8%	-56.2%	-81.7%	-64.4%
GSV, α=5	0.647	0.556	-67.2%	-52.9%	-66.9%	-48.9%	-71.7%	-54.4%	-78.3%	-58.7%
OLS, simple	0.969	0.897								

Table A.13: Oil - MEG and GSV hedge ratios

Oil			in		out, daily		out, constant		out, weekly	
	HR in	HR out	%Δ var	%Δ VaR	%Δ var	%Δ VaR	%Δ var	%Δ VaR	%Δ var	%Δ VaR
Gini, ν=1.5	1.027	1.021	-82.8%	-82.7%	-98.6%	-92.8%	-98.6%	-92.6%	-99.0%	-96.2%
Gini, ν=2	1.016	1.013	-82.9%	-83.2%	-98.7%	-92.9%	-98.7%	-92.8%	-99.1%	-96.6%
Gini, ν=5	0.995	0.999	-82.8%	-83.3%	-98.7%	-92.7%	-98.7%	-92.7%	-99.0%	-96.8%
Gini, ν=10	0.980	0.987	-82.8%	-82.7%	-98.7%	-92.4%	-98.7%	-92.3%	-99.0%	-96.4%
Gini, ν=20	0.963	0.974	-82.6%	-81.9%	-98.6%	-91.5%	-98.6%	-91.7%	-98.9%	-95.2%
Gini2, ν=1.5	1.012	1.009	-82.9%	-83.2%	-98.7%	-92.8%	-98.7%	-92.8%	-99.1%	-96.6%
Gini2, ν=2	1.012	1.009	-82.9%	-83.3%	-98.7%	-92.8%	-98.7%	-92.8%	-99.1%	-96.5%
Gini2, ν=5	1.020	1.013	-82.9%	-82.9%	-98.7%	-92.9%	-98.7%	-92.8%	-99.1%	-96.5%
Gini2, ν=10	1.030	1.020	-82.8%	-82.8%	-98.6%	-92.8%	-98.6%	-92.5%	-99.1%	-96.2%
Gini2, ν=20	1.043	1.028	-82.8%	-82.9%	-98.6%	-92.4%	-98.5%	-91.8%	-99.0%	-95.6%
GSV, α=1	1.007	1.007	-82.9%	-82.9%	-98.7%	-92.8%	-98.7%	-92.8%	-99.1%	-96.7%
GSV, α=2	1.038	1.026	-82.8%	-82.8%	-98.6%	-92.4%	-98.5%	-91.9%	-99.0%	-95.7%
GSV, α=3	1.038	1.026	-82.8%	-82.8%	-98.6%	-92.4%	-98.5%	-91.9%	-99.0%	-95.7%
GSV, α=4	1.075	1.037	-82.6%	-82.8%	-98.1%	-88.5%	-98.0%	-89.2%	-98.7%	-91.4%
GSV, α=5	0.980	0.981	-82.8%	-82.7%	-97.9%	-87.9%	-98.7%	-92.3%	-98.3%	-90.1%
OLS, simple	1.015	1.013								

Table A.14: Platinum - MEG and GSV hedge ratios

Platinum			in		out, daily		out, constant		out, weekly	
	HR in	HR out	%Δ var	%Δ VaR	%Δ var	%Δ VaR	%Δ var	%Δ VaR	%Δ var	%Δ VaR
Gini, ν=1.5	0.677	0.665	-53.4%	-38.3%	-54.6%	-30.5%	-54.5%	-29.3%	-83.4%	-55.1%
Gini, ν=2	0.687	0.671	-53.4%	-37.7%	-54.6%	-29.8%	-54.4%	-29.3%	-83.8%	-55.2%
Gini, ν=5	0.711	0.688	-53.4%	-38.5%	-54.5%	-29.4%	-54.1%	-29.7%	-84.5%	-55.3%
Gini, ν=10	0.740	0.710	-53.3%	-38.4%	-54.2%	-30.5%	-53.5%	-29.8%	-85.5%	-55.0%
Gini, ν=20	0.767	0.736	-52.9%	-38.4%	-53.7%	-30.1%	-52.8%	-29.9%	-86.4%	-55.9%
Gini2, ν=1.5	0.695	0.681	-53.4%	-37.5%	-54.6%	-29.4%	-54.3%	-29.6%	-84.2%	-55.3%
Gini2, ν=2	0.704	0.686	-53.4%	-38.5%	-54.5%	-29.7%	-54.2%	-29.9%	-84.4%	-55.3%
Gini2, ν=5	0.723	0.697	-53.4%	-38.2%	-54.4%	-29.6%	-53.9%	-30.3%	-85.0%	-55.3%
Gini2, ν=10	0.737	0.706	-53.3%	-38.2%	-54.2%	-30.3%	-53.6%	-30.0%	-85.4%	-55.1%
Gini2, ν=20	0.747	0.709	-53.2%	-38.5%	-54.2%	-30.7%	-53.3%	-29.3%	-85.5%	-55.2%
GSV, α=1	0.697	0.676	-53.5%	-38.0%	-54.5%	-29.2%	-54.3%	-29.7%	-84.1%	-55.2%
GSV, α=2	0.719	0.692	-53.4%	-38.1%	-54.4%	-29.2%	-53.9%	-29.7%	-84.8%	-55.3%
GSV, α=3	0.711	0.687	-53.4%	-38.5%	-54.4%	-29.4%	-54.1%	-29.7%	-84.6%	-55.5%
GSV, α=4	0.671	0.653	-53.4%	-38.6%	-54.3%	-29.9%	-54.5%	-30.2%	-82.8%	-54.2%
GSV, α=5	0.606	0.593	-52.5%	-38.7%	-53.3%	-29.1%	-54.3%	-27.2%	-78.9%	-51.9%
OLS, simple	0.698	0.681								

Table A.15: Soybeans - MEG and GSV hedge ratios

Soybeans			in		out, daily		out, constant		out, weekly	
	HR in	HR out	%Δ var	%Δ VaR	%Δ var	%Δ VaR	%Δ var	%Δ VaR	%Δ var	%Δ VaR
Gini, ν=1.5	0.984	0.974	-87.3%	-80.8%	-83.7%	-70.5%	-83.7%	-72.7%	-93.1%	-64.1%
Gini, ν=2	0.989	0.975	-87.3%	-80.8%	-83.7%	-70.5%	-83.7%	-73.3%	-93.1%	-64.4%
Gini, ν=5	0.998	0.974	-87.3%	-80.8%	-83.7%	-71.0%	-83.7%	-73.3%	-93.1%	-64.5%
Gini, ν=10	1.005	0.976	-87.3%	-80.6%	-83.7%	-71.3%	-83.7%	-72.7%	-93.1%	-65.0%
Gini, ν=20	1.016	0.980	-87.2%	-80.7%	-83.7%	-71.7%	-83.7%	-71.8%	-93.2%	-65.3%
Gini2, ν=1.5	1.011	1.004	-87.2%	-80.7%	-83.8%	-73.2%	-83.7%	-72.2%	-93.2%	-60.7%
Gini2, ν=2	1.012	1.004	-87.2%	-80.7%	-83.8%	-73.2%	-83.7%	-72.1%	-93.2%	-60.7%
Gini2, ν=5	1.011	1.000	-87.2%	-80.7%	-83.8%	-73.6%	-83.7%	-72.2%	-93.2%	-61.2%
Gini2, ν=10	1.003	0.992	-87.3%	-80.6%	-83.8%	-72.1%	-83.7%	-72.8%	-93.2%	-61.9%
Gini2, ν=20	0.990	0.975	-87.3%	-80.8%	-83.8%	-71.3%	-83.7%	-73.5%	-93.2%	-64.3%
GSV, α=1	1.014	1.006	-87.2%	-80.7%	-83.8%	-73.2%	-83.7%	-71.9%	-93.2%	-60.7%
GSV, α=2	0.994	0.975	-87.3%	-81.0%	-83.8%	-71.6%	-83.7%	-73.6%	-93.2%	-64.4%
GSV, α=3	0.988	0.931	-87.3%	-80.8%	-83.4%	-74.3%	-83.7%	-73.3%	-92.8%	-68.7%
GSV, α=4	0.985	0.874	-87.3%	-80.9%	-81.7%	-69.1%	-83.7%	-72.8%	-90.7%	-65.7%
GSV, α=5	0.963	0.808	-87.2%	-80.7%	-78.8%	-62.5%	-83.6%	-70.3%	-87.2%	-66.7%
OLS, simple	0.991	0.972								

Table A.16: Wheat - MEG and GSV hedge ratios

Wheat			in		out, daily		out, constant		out, weekly	
	HR in	HR out	%Δ var	%Δ VaR	%Δ var	%Δ VaR	%Δ var	%Δ VaR	%Δ var	%Δ VaR
Gini, ν=1.5	1.150	1.087	-70.2%	-58.1%	-57.2%	-61.5%	-56.0%	-59.2%	-79.2%	-59.6%
Gini, ν=2	1.160	1.093	-70.2%	-57.8%	-56.9%	-61.5%	-55.6%	-59.2%	-78.8%	-58.3%
Gini, ν=5	1.178	1.098	-70.2%	-59.2%	-56.5%	-61.5%	-54.9%	-58.2%	-78.2%	-58.2%
Gini, ν=10	1.190	1.098	-70.2%	-59.4%	-56.3%	-61.4%	-54.4%	-58.2%	-77.9%	-58.1%
Gini, ν=20	1.210	1.103	-70.1%	-59.6%	-55.9%	-60.2%	-53.5%	-58.2%	-77.2%	-57.6%
Gini2, ν=1.5	1.142	1.073	-70.2%	-58.5%	-57.5%	-62.5%	-56.3%	-59.7%	-79.8%	-60.9%
Gini2, ν=2	1.144	1.075	-70.2%	-58.4%	-57.4%	-62.2%	-56.3%	-59.5%	-79.7%	-60.6%
Gini2, ν=5	1.157	1.088	-70.2%	-57.9%	-56.8%	-61.6%	-55.7%	-59.0%	-78.7%	-58.4%
Gini2, ν=10	1.173	1.105	-70.2%	-58.6%	-56.1%	-60.7%	-55.1%	-58.4%	-77.6%	-57.5%
Gini2, ν=20	1.201	1.122	-70.1%	-59.4%	-55.2%	-59.5%	-53.9%	-58.2%	-76.1%	-55.7%
GSV, α=1	1.135	1.074	-70.2%	-58.5%	-57.4%	-63.3%	-56.6%	-60.2%	-79.6%	-60.7%
GSV, α=2	1.181	1.115	-70.2%	-59.4%	-55.7%	-60.1%	-54.8%	-58.2%	-76.9%	-56.3%
GSV, α=3	1.229	1.135	-70.0%	-60.2%	-54.4%	-58.1%	-52.5%	-57.3%	-74.9%	-54.6%
GSV, α=4	1.308	1.132	-69.1%	-58.7%	-53.1%	-54.6%	-48.1%	-50.3%	-72.8%	-53.6%
GSV, α=5	1.400	1.141	-67.2%	-56.9%	-51.1%	-50.1%	-41.8%	-44.5%	-69.4%	-46.8%
OLS, simple	1.161	1.086								

Table A.17: Beef Overview I

Beef	No	Naive	OLS,si	OLS,sp	ECM,si	ECM,sp	GARCH,si	GARCH,sp	bGARCH,si	bGARCH,sp	bGARCH,si,a	bGARCH,sp,a
in-sample												
M. revenues	0.00023	0.00054	0.00024	0.00024	0.00024	0.00025	0.00024	-	0.00024	0.00024	0.00024	0.00024
Variance	0.00003	0.00011	0.00003	0.00003	0.00003	0.00003	0.00003	-	0.00003	0.00003	0.00003	0.00003
Variance red.	-	214.87%	-0.44%	-0.41%	-0.43%	-0.37%	-0.43%	-	-0.30%	-0.36%	-0.43%	-0.39%
VaR	0.00823	0.01633	0.00822	0.00823	0.00822	0.00823	0.00822	-	0.00823	0.00823	0.00822	0.00823
VaR red.	-	98.43%	-0.09%	0.00%	-0.06%	0.05%	-0.11%	-	-0.04%	0.04%	-0.07%	0.03%
VaR, perc.	0.00834	0.01582	0.00848	0.00844	0.00846	0.00852	0.00847	-	0.00844	0.00839	0.00846	0.00848
VaR, perc., red.	-	89.69%	1.70%	1.23%	1.41%	2.17%	1.61%	-	1.18%	0.58%	1.51%	1.70%
Δ skewness	-	-0.3909	-0.0016	-0.0034	-0.0022	-0.0043	-0.0012	-	-0.0005	-0.0042	-0.0021	-0.0039
Δ kurtosis	-	-2.363	-0.064	-0.088	-0.073	-0.101	-0.057	-	-0.071	-0.091	-0.071	-0.095
out-of sample, daily												
M. revenues	0.00001	0.00023	0.00002	0.00002	0.00002	0.00003	0.00002	-	0.00003	0.00003	-	-
Variance	0.00003	0.00009	0.00003	0.00003	0.00003	0.00003	0.00003	-	0.00003	0.00003	-	-
Variance red.	-	193.93%	-0.41%	-0.41%	-0.41%	-0.42%	-0.44%	-	-0.42%	-0.49%	-	-
VaR	0.00067	0.00009	0.00067	0.00067	0.00067	0.00067	0.00067	-	0.00068	0.00068	-	-
VaR red.	-	-86.47%	0.59%	0.65%	0.50%	0.66%	0.53%	-	1.76%	1.44%	-	-
VaR, perc.	0.00850	0.01497	0.00839	0.00849	0.00843	0.00851	0.00834	-	0.00837	0.00846	-	-
VaR, perc., red.	-	76.06%	-1.25%	-0.19%	-0.86%	0.11%	-1.94%	-	-1.55%	-0.43%	-	-
Δ skewness	-	-0.6747	0.0058	0.0062	0.0052	0.0064	0.0055	-	0.0145	0.0123	-	-
Δ kurtosis	-	-4.494	0.042	0.042	0.042	0.043	0.045	-	0.073	0.055	-	-
out-of sample, constant												
M. revenues	0.00001	0.00023	0.00002	0.00003	0.00002	0.00003	0.00002	-	0.00002	0.00002	0.00002	0.00003
Variance	0.00003	0.00009	0.00003	0.00003	0.00003	0.00003	0.00003	-	0.00003	0.00003	0.00003	0.00003
Variance red.	-	193.93%	-0.51%	-0.51%	-0.52%	-0.49%	-0.50%	-	-0.50%	-0.51%	-0.52%	-0.50%
VaR	0.00067	0.00009	0.00717	0.00717	0.00717	0.00717	0.00717	-	0.00717	0.00717	0.00717	0.00717
VaR red.	-	-86.47%	-0.51%	-0.52%	-0.52%	-0.50%	-0.50%	-	-0.50%	-0.51%	-0.52%	-0.51%
VaR, perc.	0.00850	0.01497	0.00839	0.00849	0.00843	0.00852	0.00836	-	0.00835	0.00840	0.00842	0.00851
VaR, perc., red.	-	76.06%	-1.36%	-0.16%	-0.89%	0.23%	-1.72%	-	-1.73%	-1.18%	-0.99%	0.06%
Δ skewness	-	-0.6747	-0.6747	0.0072	0.0075	0.0074	0.0074	-	0.0070	0.0070	0.0073	0.0073
Δ kurtosis	-	-4.494	-4.494	0.056	0.055	0.056	0.052	-	0.055	0.055	0.056	0.056
out-of sample,weekly												
M. revenues	0.00001	0.00023	0.00002	0.00002	0.00002	0.00003	0.00002	-	0.00003	0.00003	-	-
Variance	0.00003	0.00009	0.00003	0.00003	0.00003	0.00003	0.00003	-	0.00003	0.00003	-	-
Variance red.	-	193.93%	-0.46%	-0.45%	-0.46%	-0.46%	-0.49%	-	-0.49%	-0.50%	-	-
VaR	0.00720	0.01510	0.00717	0.00717	0.00717	0.00717	0.00717	-	0.00716	0.00716	-	-
VaR red.	-	109.53%	-0.42%	-0.43%	-0.41%	-0.44%	-0.44%	-	-0.61%	-0.57%	-	-
VaR, perc.	0.00850	0.01497	0.00839	0.00849	0.00843	0.00851	0.00833	-	0.00836	0.00845	-	-
VaR, perc., red.	-	76.06%	-1.27%	-0.19%	-0.88%	0.11%	-1.96%	-	-1.62%	-0.55%	-	-
Δ skewness	-	-0.6747	0.0054	0.0058	0.0047	0.0059	0.0050	-	0.0114	0.0106	-	-
Δ kurtosis	-	-4.494	0.044	0.044	0.044	0.045	0.049	-	0.060	0.045	-	-

Table A.18: Beef Overview II

Beef	Sharpe	Gini 1.5	Gini 2	Gini 5	Gini 10	Gini 20	Gini2 1.5	Gini2 2	Gini2 5	Gini2 10	Gini2 20	GSV 1	GSV 2	GSV 3	GSV 4	GSV 5	VaR
in-sample																	
M. revenues	-	0.00024	0.00024	0.00024	0.00024	0.00024	0.00024	0.00024	0.00024	0.00024	0.00024	0.00024	0.00025	0.00025	0.00026	0.00026	0.00024
Variance	-	0.00003	0.00003	0.00003	0.00003	0.00003	0.00003	0.00003	0.00003	0.00003	0.00003	0.00003	0.00003	0.00003	0.00003	0.00003	0.00003
Variance red.	-	-0.44%	-0.44%	-0.44%	-0.44%	-0.42%	-0.40%	-0.40%	-0.42%	-0.44%	-0.41%	-0.44%	-0.38%	-0.17%	0.17%	0.51%	-0.44%
VaR	-	0.00822	0.00822	0.00822	0.00822	0.00822	0.00822	0.00822	0.00822	0.00822	0.00823	0.00822	0.00823	0.00826	0.00828	0.00831	0.00822
VaR red.	-	-0.09%	-0.09%	-0.09%	-0.10%	-0.13%	-0.13%	-0.13%	-0.13%	-0.10%	-0.01%	-0.09%	0.05%	0.31%	0.67%	0.99%	-0.10%
VaR, perc.	-	0.00848	0.00848	0.00848	0.00848	0.00839	0.00835	0.00833	0.00840	0.00848	0.00844	0.00848	0.00851	0.00846	0.00842	0.00830	0.00848
VaR, perc., red.	-	1.69%	1.71%	1.71%	1.71%	0.67%	0.13%	-0.07%	0.77%	1.71%	1.18%	1.71%	2.12%	1.50%	1.01%	-0.50%	1.71%
Δ skewness	-	-0.0017	-0.0016	-0.0016	-0.0014	-0.0007	-0.0004	-0.0003	-0.0007	-0.0014	-0.0033	-0.0016	-0.0043	-0.0083	-0.0134	-0.0178	-0.0014
Δ kurtosis	-	-0.064	-0.062	-0.062	-0.060	-0.047	-0.042	-0.040	-0.048	-0.059	-0.088	-0.062	-0.100	-0.146	-0.198	-0.240	-0.060
out-of sample, daily																	
M. revenues	-	0.00002	0.00002	0.00002	0.00002	0.00002	0.00002	0.00002	0.00002	0.00002	0.00003	0.00002	0.00003	0.00003	0.00004	0.00004	0.00002
Variance	-	0.00003	0.00003	0.00003	0.00003	0.00003	0.00003	0.00003	0.00003	0.00003	0.00003	0.00003	0.00003	0.00003	0.00003	0.00003	0.00003
Variance red.	-	-0.58%	-0.56%	-0.52%	-0.48%	-0.40%	-0.50%	-0.49%	-0.52%	-0.57%	-0.58%	-0.40%	-0.44%	-0.41%	-0.20%	0.20%	-0.45%
VaR	-	0.00067	0.00067	0.00067	0.00067	0.00067	0.00067	0.00067	0.00067	0.00068	0.00068	0.00067	0.00067	0.00067	0.00067	0.00067	0.00717
VaR red.	-	0.63%	0.61%	0.55%	0.60%	0.72%	0.55%	0.62%	0.90%	1.10%	1.04%	-0.04%	0.54%	0.68%	0.74%	0.75%	-0.48%
VaR, perc.	-	0.00839	0.00839	0.00836	0.00836	0.00830	0.00832	0.00831	0.00833	0.00835	0.00843	0.00845	0.00855	0.00846	0.00834	0.00845	0.00837
VaR, perc., red.	-	-1.25%	-1.36%	-1.68%	-1.71%	-2.32%	-2.17%	-2.30%	-1.98%	-1.73%	-0.79%	-0.60%	0.54%	-0.49%	-1.92%	-0.56%	-1.51%
Δ skewness	-	0.0068	0.0065	0.0060	0.0062	0.0068	0.0059	0.0064	0.0085	0.0101	0.0098	0.0012	0.0056	0.0065	0.0062	0.0048	0.0076
Δ kurtosis	-	0.055	0.051	0.044	0.043	0.039	0.048	0.048	0.053	0.058	0.057	0.033	0.041	0.033	0.004	-0.047	0.052
out-of sample, constant																	
M. revenues	-	0.00002	0.00002	0.00002	0.00002	0.00002	0.00002	0.00002	0.00002	0.00002	0.00003	0.00002	0.00003	0.00003	0.00003	0.00004	0.00002
Variance	-	0.00003	0.00003	0.00003	0.00003	0.00003	0.00003	0.00003	0.00003	0.00003	0.00003	0.00003	0.00003	0.00003	0.00003	0.00003	0.00003
Variance red.	-	-0.51%	-0.51%	-0.51%	-0.50%	-0.47%	-0.45%	-0.44%	-0.47%	-0.50%	-0.51%	-0.51%	-0.49%	-0.35%	-0.08%	0.19%	-0.50%
VaR	-	0.00717	0.00717	0.00717	0.00717	0.00717	0.00717	0.00717	0.00717	0.00717	0.00717	0.00717	0.00717	0.00718	0.00720	0.00721	0.00717
VaR red.	-	-0.51%	-0.51%	-0.51%	-0.50%	-0.47%	-0.45%	-0.44%	-0.47%	-0.50%	-0.52%	-0.51%	-0.50%	-0.37%	-0.12%	0.14%	-0.50%
VaR, perc.	-	0.00839	0.00838	0.00838	0.00837	0.00830	0.00829	0.00830	0.00831	0.00837	0.00849	0.00838	0.00852	0.00839	0.00838	0.00845	0.00837
VaR, perc., red.	-	-1.33%	-1.43%	-1.44%	-1.56%	-2.32%	-2.52%	-2.33%	-2.26%	-1.60%	-0.18%	-1.44%	0.22%	-1.35%	-1.44%	-0.56%	-1.55%
Δ skewness	-	0.0075	0.0072	0.0071	0.0071	0.0071	0.0065	0.0062	0.0060	0.0065	0.0070	0.0075	0.0071	0.0074	0.0061	0.0033	0.0003
Δ kurtosis	-	0.054	0.056	0.056	0.056	0.055	0.052	0.050	0.049	0.052	0.055	0.055	0.056	0.053	0.034	0.001	-0.033
out-of sample,weekly																	
M. revenues	-	0.00002	0.00002	0.00002	0.00002	0.00002	0.00002	0.00002	0.00002	0.00002	0.00003	0.00002	0.00003	0.00003	0.00004	0.00004	0.00002
Variance	-	0.00003	0.00003	0.00003	0.00003	0.00003	0.00003	0.00003	0.00003	0.00003	0.00003	0.00003	0.00003	0.00003	0.00003	0.00003	0.00003
Variance red.	-	-0.52%	-0.50%	-0.46%	-0.43%	-0.37%	-0.45%	-0.44%	-0.45%	-0.48%	-0.50%	-0.35%	-0.38%	-0.32%	-0.12%	0.27%	-0.45%
VaR	-	0.00717	0.00717	0.00717	0.00718	0.00718	0.00717	0.00717	0.00717	0.00717	0.00717	0.00719	0.00718	0.00718	0.00719	0.00722	0.00717
VaR red.	-	-0.47%	-0.46%	-0.42%	-0.40%	-0.37%	-0.41%	-0.42%	-0.46%	-0.51%	-0.49%	-0.24%	-0.34%	-0.30%	-0.14%	0.16%	-0.46%
VaR, perc.	-	0.00840	0.00839	0.00837	0.00836	0.00831	0.00832	0.00831	0.00835	0.00837	0.00845	0.00846	0.00856	0.00848	0.00836	0.00846	0.00834
VaR, perc., red.	-	-1.17%	-1.28%	-1.60%	-1.62%	-2.24%	-2.12%	-2.23%	-1.84%	-1.52%	-0.66%	-0.53%	0.71%	-0.31%	-1.72%	-0.50%	-1.86%
Δ skewness	-	0.0058	0.0058	0.0055	0.0055	0.0056	0.0052	0.0056	0.0071	0.0079	0.0070	0.0009	0.0040	0.0040	0.0034	0.0022	0.0068
Δ kurtosis	-	0.051	0.047	0.041	0.039	0.034	0.043	0.043	0.046	0.050	0.050	0.026	0.035	0.027	-0.001	-0.050	0.048

Table A.19: Coffee Overview I

Coffee	No	Naive	OLS,si	OLS,sp	ECM,si	ECM,sp	GARCH,si	GARCH,sp	bGARCH,si	bGARCH,sp	bGARCH,si,a	bGARCH,sp,a
in-sample												
M. revenues	0.00103	0.00026	0.00104	0.00101	-	-	0.00108	0.00101	0.00104	-	0.00104	-
Variance	0.00020	0.00057	0.00020	0.00020	-	-	0.00020	0.00020	0.00020	-	0.00020	-
Variance red.	-	182.09%	0.00%	0.14%	-	-	0.55%	0.23%	0.00%	-	0.00%	-
VaR	0.02400	0.03885	0.02400	0.02400	-	-	0.02411	0.02400	0.02400	-	0.02400	-
VaR reduction	-	61.91%	0.01%	0.00%	-	-	0.46%	0.02%	0.02%	-	0.03%	-
VaR, perc.	0.02046	0.03782	0.02051	0.02096	-	-	0.02151	0.02115	0.02059	-	0.02054	-
VaR, perc., red.	-	84.89%	0.25%	2.48%	-	-	5.15%	3.36%	0.64%	-	0.38%	-
Δ skewness	-	0.4493	-0.0002	0.0024	-	-	-0.0024	0.0033	-0.0003	-	-0.0006	-
Δ kurtosis	-	-3.101	-0.005	0.027	-	-	-0.124	0.032	-0.012	-	-0.012	-
out-of sample, daily												
M. revenues	-0.00138	0.00037	-0.00136	-0.00134	-	-	-0.00141	-0.00136	-0.00140	-	-	-
Variance	0.00022	0.00059	0.00022	0.00022	-	-	0.00022	0.00022	0.00022	-	-	-
Variance red.	-	165.37%	0.26%	0.33%	-	-	0.45%	0.11%	-0.14%	-	-	-
VaR	0.02485	0.03940	0.02489	0.02490	-	-	0.02490	0.02486	0.02482	-	-	-
VaR reduction	-	58.59%	0.18%	0.21%	-	-	0.21%	0.06%	-0.11%	-	-	-
VaR, perc.	0.02775	0.04157	0.02756	0.02764	-	-	0.02771	0.02756	0.02754	-	-	-
VaR, perc., red.	-	49.77%	-0.69%	-0.41%	-	-	-0.15%	-0.69%	-0.78%	-	-	-
Δ skewness	-	0.1755	-0.0019	-0.0020	-	-	0.0004	0.0000	0.0019	-	-	-
Δ kurtosis	-	-0.286	-0.016	-0.014	-	-	0.008	-0.008	0.006	-	-	-
out-of sample, constant												
M. revenues	-0.00138	0.00037	-0.00139	-0.00134	-	-	-0.00149	-0.00133	-0.00140	-	-0.00140	-
Variance	0.00022	0.00059	0.00022	0.00022	-	-	0.00022	0.00022	0.00022	-	0.00022	-
Variance red.	-	165.37%	-0.04%	0.39%	-	-	-0.17%	0.55%	-0.09%	-	-0.09%	-
VaR	0.02485	0.03940	0.02484	0.02491	-	-	0.02477	0.02494	0.02483	-	0.02483	-
VaR red.	-	58.59%	-0.03%	0.26%	-	-	-0.30%	0.36%	-0.07%	-	-0.07%	-
VaR, perc.	0.02775	0.04157	0.02775	0.02775	-	-	0.02646	0.02796	0.02764	-	0.02764	-
VaR, perc., red.	-	49.77%	0.00%	-0.01%	-	-	-4.67%	0.73%	-0.43%	-	-0.42%	-
Δ skewness	-	0.1755	0.1755	0.0005	-	-	0.0054	0.0104	-0.0037	-	0.0012	-
Δ kurtosis	-	-0.286	-0.286	0.002	-	-	0.0179	0.034	-0.020	-	0.005	-
out-of sample,weekly												
M. revenues	-0.00138	0.00037	-0.00136	-0.00134	-	-	-0.00141	-0.00136	-0.00140	-	-	-
Variance	0.00022	0.00059	0.00022	0.00022	-	-	0.00022	0.00022	0.00022	-	-	-
Variance red.	-	165.37%	0.16%	0.30%	-	-	0.38%	0.08%	-0.12%	-	-	-
VaR	0.02485	0.03940	0.02488	0.02490	-	-	0.02489	0.02486	0.02482	-	-	-
VaR red.	-	58.59%	0.14%	0.20%	-	-	0.19%	0.05%	-0.10%	-	-	-
VaR, perc.	0.02775	0.04157	0.02753	0.02763	-	-	0.02767	0.02753	0.02752	-	-	-
VaR, perc., red.	-	49.77%	-0.81%	-0.46%	-	-	-0.31%	-0.79%	-0.83%	-	-	-
Δ skewness	-	0.1755	-0.0024	-0.0022	-	-	-0.0007	-0.0001	0.0017	-	-	-
Δ kurtosis	-	-0.286	-0.015	-0.014	-	-	0.009	-0.007	0.007	-	-	-

Table A.20: Coffee Overview II

Coffee	Sharpe	Gini 1.5	Gini 2	Gini 5	Gini 10	Gini 20	Gini2 1.5	Gini2 2	Gini2 5	Gini2 10	Gini2 20	GSV 1	GSV 2	GSV 3	GSV 4	GSV 5	VaR
in-sample																	
M. revenues	-	0.00106	0.00105	0.00103	0.00102	0.00101	0.00103	0.00103	0.00102	0.00101	0.00100	0.00105	0.00103	0.00105	0.00111	0.00111	0.00103
Variance	-	0.00020	0.00020	0.00020	0.00020	0.00020	0.00020	0.00020	0.00020	0.00020	0.00020	0.00020	0.00020	0.00020	0.00020	0.00020	0.00020
Variance red.	-	0.12%	0.10%	0.00%	0.09%	0.24%	0.00%	0.00%	0.07%	0.22%	0.42%	0.09%	0.00%	0.10%	1.54%	1.69%	0.00%
VaR	-	0.02403	0.02403	0.02400	0.02399	0.02400	0.02400	0.02400	0.02399	0.02400	0.02402	0.02403	0.02400	0.02403	0.02426	0.02428	0.02400
VaR reduction	-	0.15%	0.14%	0.00%	-0.01%	0.03%	0.01%	0.01%	-0.01%	0.02%	0.09%	0.12%	0.01%	0.13%	1.09%	1.18%	0.00%
VaR, perc.	-	0.02099	0.02093	0.02048	0.02093	0.02117	0.02049	0.02049	0.02086	0.02113	0.02124	0.02085	0.02049	0.02088	0.02193	0.02200	0.02046
VaR, perc., red.	-	2.58%	2.29%	0.09%	2.30%	3.47%	0.18%	0.18%	1.97%	3.28%	3.85%	1.92%	0.18%	2.08%	7.21%	7.55%	0.03%
Δ skewness	-	-0.0017	-0.0017	-0.0001	0.0018	0.0034	-0.0002	-0.0002	0.0014	0.0032	0.0050	-0.0016	-0.0002	-0.0016	-0.0018	-0.0017	0.0000
Δ kurtosis	-	-0.051	-0.048	-0.002	0.022	0.033	-0.003	-0.003	0.019	0.032	0.037	-0.045	-0.003	-0.047	-0.240	-0.255	-0.001
out-of sample, daily																	
M. revenues	-	-0.00139	-0.00139	-0.00136	-0.00133	-0.00132	-0.00136	-0.00136	-0.00135	-0.00135	-0.00134	-0.00135	-0.00136	-0.00138	-0.00146	-0.00152	-0.00137
Variance	-	0.00022	0.00022	0.00022	0.00022	0.00022	0.00022	0.00022	0.00022	0.00022	0.00022	0.00022	0.00022	0.00022	0.00022	0.00022	0.00022
Variance red.	-	-0.01%	-0.12%	-0.12%	0.12%	0.25%	0.03%	0.03%	-0.13%	-0.36%	-0.28%	0.43%	-0.03%	-0.13%	0.32%	0.43%	-0.14%
VaR	-	0.02485	0.02484	0.02485	0.02489	0.02490	0.02487	0.02487	0.02484	0.02480	0.02481	0.02492	0.02485	0.02482	0.02484	0.02481	0.02483
VaR reduction	-	0.03%	-0.04%	0.01%	0.17%	0.23%	0.09%	0.09%	-0.03%	-0.18%	-0.16%	0.30%	0.00%	-0.12%	-0.04%	-0.16%	-0.06%
VaR, perc.	-	0.02774	0.02769	0.02739	0.02723	0.02735	0.02747	0.02747	0.02718	0.02706	0.02700	0.02813	0.02730	0.02774	0.02737	0.02678	0.02741
VaR, perc., red.	-	-0.05%	-0.22%	-1.30%	-1.88%	-1.46%	-1.03%	-1.03%	-2.07%	-2.50%	-2.73%	1.36%	-1.65%	-0.06%	-1.37%	-3.52%	-1.24%
Δ skewness	-	-0.0016	-0.0011	-0.0025	-0.0043	-0.0040	-0.0031	-0.0031	-0.0011	0.0011	0.0022	-0.0040	0.0000	0.0037	0.0105	0.0191	-0.0008
Δ kurtosis	-	-0.007	-0.006	-0.020	-0.029	-0.032	-0.017	-0.017	-0.017	-0.013	-0.015	-0.013	-0.011	-0.002	0.019	0.047	0.000
out-of sample, constant																	
M. revenues	-	-0.00143	-0.00143	-0.00138	-0.00135	-0.00132	-0.00139	-0.00139	-0.00135	-0.00133	-0.00130	-0.00143	-0.00139	-0.00143	-0.00155	-0.00156	-0.00138
Variance	-	0.00022	0.00022	0.00022	0.00022	0.00022	0.00022	0.00022	0.00022	0.00022	0.00023	0.00022	0.00022	0.00022	0.00022	0.00022	0.00022
Variance red.	-	-0.22%	-0.21%	-0.01%	0.29%	0.57%	-0.03%	-0.03%	0.23%	0.54%	0.85%	-0.21%	-0.03%	-0.21%	0.27%	0.35%	0.00%
VaR	-	0.02480	0.02480	0.02484	0.02490	0.02494	0.02484	0.02484	0.02489	0.02493	0.02498	0.02480	0.02484	0.02480	0.02478	0.02479	0.02485
VaR red.	-	-0.21%	-0.20%	-0.01%	0.20%	0.37%	-0.02%	-0.02%	0.16%	0.35%	0.54%	-0.19%	-0.02%	-0.19%	-0.26%	-0.24%	0.00%
VaR, perc.	-	0.02710	0.02715	0.02776	0.02783	0.02798	0.02777	0.02777	0.02778	0.02794	0.02828	0.02720	0.02777	0.02718	0.02667	0.02667	0.02776
VaR, perc., red.	-	-2.37%	-2.19%	0.02%	0.27%	0.81%	0.04%	0.04%	0.09%	0.67%	1.89%	-1.99%	0.04%	-2.07%	-3.91%	-3.89%	0.01%
Δ skewness	-	0.0047	0.0046	0.0043	0.0002	-0.0024	-0.0038	0.0003	0.0003	-0.0020	-0.0037	-0.0048	0.0040	0.0003	0.0042	0.0193	0.0204
Δ kurtosis	-	0.017	0.017	0.016	0.001	-0.012	-0.021	0.001	0.001	-0.010	-0.020	-0.028	0.015	0.001	0.016	0.053	0.055
out-of sample,weekly																	
M. revenues	-	-0.00139	-0.00139	-0.00136	-0.00133	-0.00132	-0.00136	-0.00136	-0.00135	-0.00135	-0.00134	-0.00135	-0.00136	-0.00139	-0.00146	-0.00153	-0.00137
Variance	-	0.00022	0.00022	0.00022	0.00022	0.00022	0.00022	0.00022	0.00022	0.00022	0.00022	0.00022	0.00022	0.00022	0.00022	0.00022	0.00022
Variance red.	-	0.08%	-0.04%	-0.03%	0.22%	0.34%	0.10%	0.10%	-0.07%	-0.29%	-0.19%	0.49%	0.03%	-0.04%	0.42%	0.49%	-0.19%
VaR	-	0.02486	0.02485	0.02486	0.02490	0.02491	0.02488	0.02488	0.02485	0.02482	0.02483	0.02493	0.02486	0.02484	0.02486	0.02482	0.02483
VaR red.	-	0.07%	0.00%	0.05%	0.21%	0.27%	0.12%	0.12%	0.03%	-0.11%	-0.06%	0.32%	0.06%	-0.03%	0.07%	-0.10%	-0.06%
VaR, perc.	-	0.02775	0.02771	0.02740	0.02724	0.02737	0.02748	0.02748	0.02719	0.02707	0.02702	0.02809	0.02731	0.02776	0.02746	0.02678	0.02759
VaR, perc., red.	-	-0.01%	-0.15%	-1.29%	-1.86%	-1.39%	-1.00%	-1.00%	-2.05%	-2.46%	-2.66%	1.21%	-1.60%	0.01%	-1.06%	-3.52%	-0.59%
Δ skewness	-	-0.0014	-0.0009	-0.0023	-0.0038	-0.0036	-0.0031	-0.0031	-0.0023	-0.0010	-0.0010	-0.0037	-0.0017	0.0006	0.0063	0.0167	-0.0013
Δ kurtosis	-	-0.006	-0.005	-0.018	-0.027	-0.028	-0.018	-0.018	-0.018	-0.012	-0.013	-0.014	-0.011	0.001	0.026	0.053	-0.008

Table A.21: Copper Overview I

Copper	No	Naive	OLS,si	OLS,sp	ECM,si	ECM,sp	GARCH,si	GARCH,sp	bGARCH,si	bGARCH,sp	bGARCH,si,a	bGARCH,sp,a
in-sample												
Mean revenues	0.00015	0.00006	0.00006	0.00006	0.00006	0.00006	-	-	0.00007	0.00006	0.00006	0.00006
Variance	0.00057	0.00005	0.00005	0.00005	0.00005	0.00005	-	-	0.00005	0.00004	0.00005	0.00005
Variance reduction	-	-91.79%	-91.88%	-91.87%	-91.87%	-91.87%	-	-	-92.12%	-92.44%	-91.87%	-91.86%
VaR	0.03931	0.00518	0.00532	0.00529	0.00528	0.00526	-	-	0.00628	0.00595	0.00539	0.00523
VaR reduction	-	-86.83%	-86.46%	-86.55%	-86.56%	-86.62%	-	-	-84.04%	-84.86%	-86.30%	-86.70%
VaR, percentile	0.03829	0.00374	0.00380	0.00368	0.00367	0.00363	-	-	0.00465	0.00409	0.00400	0.00358
VaR, per, reduction	-	-90.22%	-90.07%	-90.39%	-90.42%	-90.51%	-	-	-87.87%	-89.33%	-89.55%	-90.64%
Δ skewness	-	-0.5179	-0.3911	-0.4077	-0.4115	-0.4239	-	-	-1.2509	-0.7380	-0.3647	-0.4451
Δ kurtosis	-	50.892	47.995	48.462	48.565	48.892	-	-	50.983	46.290	47.204	49.423
out-of sample, daily												
Mean revenues	-0.00044	0.00005	0.00004	0.00004	0.00004	0.00004	-	-	0.00001	0.00006	-	-
Variance	0.00027	0.00003	0.00003	0.00003	0.00003	0.00003	-	-	0.00003	0.00003	-	-
Variance reduction	-	-90.34%	-90.25%	-90.28%	-90.29%	-90.30%	-	-	-90.10%	-90.40%	-	-
VaR	0.02615	0.00378	0.00386	0.00384	0.00383	0.00382	-	-	0.00411	0.00308	-	-
VaR reduction	-	-85.55%	-85.25%	-85.33%	-85.34%	-85.38%	-	-	-84.29%	-88.22%	-	-
VaR, percentile	0.02643	0.00148	0.00166	0.00162	0.00160	0.00156	-	-	0.00251	0.00194	-	-
VaR, per, reduction	-	-94.39%	-93.72%	-93.87%	-93.95%	-94.11%	-	-	-90.52%	-92.65%	-	-
Δ skewness	-	0.1235	0.1140	0.1129	0.1092	0.1105	-	-	0.2440	0.6366	-	-
Δ kurtosis	-	40.810	40.354	40.505	40.562	40.639	-	-	36.329	39.969	-	-
out-of sample, constant												
Mean revenues	-0.00044	0.00005	0.00004	0.00004	0.00004	0.00004	-	-	0.00003	0.00004	0.00004	0.00004
Variance	0.00027	0.00003	0.00003	0.00003	0.00003	0.00003	-	-	0.00003	0.00003	0.00003	0.00003
Variance reduction	-	-90.34%	-90.46%	-90.46%	-90.46%	-90.45%	-	-	-90.45%	-90.47%	-90.47%	-90.43%
VaR	0.02615	0.00378	0.00385	0.00383	0.00382	0.00381	-	-	0.00398	0.00389	0.00389	0.00380
VaR reduction	-	-85.55%	-85.27%	-85.35%	-85.36%	-85.41%	-	-	-84.75%	-85.12%	-85.13%	-85.48%
VaR, percentile	0.02643	0.00148	0.00173	0.00163	0.00161	0.00155	-	-	0.00199	0.00183	0.00183	0.00151
VaR, per, reduction	-	-94.39%	-93.45%	-93.83%	-93.90%	-94.13%	-	-	-92.45%	-93.08%	-93.08%	-94.27%
Δ skewness	-	0.1235	0.0423	0.0523	0.0547	0.0623	-	-	-0.0048	0.0256	0.0265	0.0756
Δ kurtosis	-	40.810	41.006	41.070	41.081	41.109	-	-	40.357	40.842	40.854	41.122
out-of sample,weekly												
M. revenues	-0.00044	0.00005	0.00004	0.00004	0.00004	0.00004	-	-	0.00000	0.00001	-	-
Variance	0.00027	0.00003	0.00003	0.00003	0.00003	0.00003	-	-	0.00003	0.00003	-	-
Variance red.	-	-90.34%	-90.26%	-90.28%	-90.30%	-90.31%	-	-	-90.13%	-90.43%	-	-
VaR	0.02613	0.00378	0.00386	0.00384	0.00384	0.00382	-	-	0.00398	0.00400	-	-
VaR red.	-	-85.55%	-85.24%	-85.31%	-85.32%	-85.37%	-	-	-84.78%	-84.70%	-	-
VaR, perc.	0.02643	0.00148	0.00166	0.00162	0.00160	0.00155	-	-	0.00224	0.00205	-	-
VaR, perc., red.	-	-94.39%	-93.72%	-93.87%	-93.94%	-94.12%	-	-	-91.54%	-92.23%	-	-
Δ skewness	-	0.1235	0.1103	0.1094	0.1051	0.1067	-	-	0.2696	-0.0739	-	-
Δ kurtosis	-	40.810	40.358	40.508	40.565	40.642	-	-	37.151	41.236	-	-

Table A.22: Copper Overview II

Copper	Sharpe	Gini 1.5	Gini 2	Gini 5	Gini 10	Gini 20	Gini2 1.5	Gini2 2	Gini2 5	Gini2 10	Gini2 20	GSV 1	GSV 2	GSV 3	GSV 4	GSV 5	VaR
in-sample																	
M. revenues	0.00007	0.00006	0.00006	0.00006	0.00006	0.00006	0.00006	0.00006	0.00006	0.00006	0.00006	0.00006	0.00006	0.00008	0.00008	0.00009	0.00006
Variance	0.00006	0.00005	0.00005	0.00005	0.00005	0.00005	0.00005	0.00005	0.00005	0.00005	0.00005	0.00005	0.00005	0.00006	0.00008	0.00009	0.00005
Variance red.	-90.34%	-91.88%	-91.88%	-91.87%	-91.87%	-91.87%	-91.79%	-91.79%	-91.79%	-91.80%	-91.84%	-91.79%	-91.86%	-89.66%	-86.35%	-84.12%	-91.79%
VaR	0.00837	0.00534	0.00531	0.00525	0.00524	0.00524	0.00518	0.00518	0.00518	0.00518	0.00519	0.00518	0.00545	0.00923	0.01231	0.01387	0.00518
VaR red.	-78.71%	-86.41%	-86.50%	-86.64%	-86.66%	-86.66%	-86.83%	-86.83%	-86.83%	-86.82%	-86.79%	-86.83%	-86.14%	-76.52%	-68.69%	-64.73%	-86.83%
VaR, perc.	0.00772	0.00385	0.00376	0.00364	0.00362	0.00361	0.00367	0.00370	0.00371	0.00363	0.00369	0.00374	0.00403	0.00863	0.01260	0.01452	0.00375
VaR, perc., red.	-79.84%	-89.94%	-90.18%	-90.50%	-90.56%	-90.56%	-90.41%	-90.33%	-90.30%	-90.51%	-90.37%	-90.22%	-89.47%	-77.46%	-67.10%	-62.08%	-90.20%
Δ skewness	0.1062	-0.3824	-0.3983	-0.4287	-0.4345	-0.4351	-0.5132	-0.5152	-0.5160	-0.5093	-0.4792	-0.5179	-0.3415	0.1628	0.2434	0.2401	-0.5186
Δ kurtosis	24.149	47.740	48.201	49.018	49.163	49.178	50.816	50.848	50.861	50.749	50.183	50.892	46.463	19.677	8.980	5.969	50.902
out-of sample, daily																	
M. revenues	0.00009	0.00004	0.00004	0.00004	0.00004	0.00004	0.00005	0.00005	0.00005	0.00005	0.00005	0.00005	0.00004	-0.00002	-0.00005	-0.00002	0.00005
Variance	0.00004	0.00003	0.00003	0.00003	0.00003	0.00003	0.00003	0.00003	0.00003	0.00003	0.00003	0.00003	0.00003	0.00003	0.00004	0.00004	0.00003
Variance red.	-86.47%	-90.29%	-90.31%	-90.32%	-90.28%	-90.23%	-90.33%	-90.33%	-90.33%	-90.32%	-90.30%	-90.33%	-90.18%	-88.24%	-85.71%	-83.73%	-90.33%
VaR	0.00693	0.00386	0.00385	0.00382	0.00382	0.00382	0.00378	0.00378	0.00378	0.00378	0.00379	0.00378	0.00391	0.00565	0.00735	0.00840	0.00378
VaR red.	-73.48%	-85.23%	-85.29%	-85.39%	-85.39%	-85.38%	-85.54%	-85.55%	-85.54%	-85.54%	-85.50%	-85.55%	-85.06%	-78.40%	-71.91%	-67.86%	-85.54%
VaR, perc.	0.00601	0.00168	0.00164	0.00156	0.00155	0.00153	0.00148	0.00147	0.00146	0.00145	0.00144	0.00146	0.00181	0.00481	0.00690	0.00809	0.00151
VaR, perc., red.	-77.27%	-93.65%	-93.78%	-94.11%	-94.14%	-94.20%	-94.42%	-94.44%	-94.48%	-94.52%	-94.54%	-94.46%	-93.13%	-81.80%	-73.88%	-69.39%	-94.29%
Δ skewness	0.1442	0.0978	0.0973	0.1064	0.1190	0.1360	0.1245	0.1253	0.1270	0.1282	0.1285	0.1257	0.1175	0.0894	0.0768	0.0697	0.1252
Δ kurtosis	20.142	40.448	40.575	40.681	40.579	40.390	40.796	40.790	40.773	40.749	40.680	40.784	39.939	28.166	19.350	15.178	40.776
out-of sample, constant																	
M. revenues	-0.00002	0.00004	0.00004	0.00004	0.00004	0.00004	0.00005	0.00005	0.00005	0.00005	0.00005	0.00005	0.00003	-0.00004	-0.00008	-0.00010	0.00005
Variance	0.00003	0.00003	0.00003	0.00003	0.00003	0.00003	0.00003	0.00003	0.00003	0.00003	0.00003	0.00003	0.00003	0.00003	0.00004	0.00005	0.00003
Variance red.	-89.09%	-90.46%	-90.46%	-90.45%	-90.44%	-90.44%	-90.35%	-90.34%	-90.34%	-90.35%	-90.40%	-90.34%	-90.46%	-88.44%	-85.24%	-83.07%	-90.34%
VaR	0.00595	0.00386	0.00384	0.00381	0.00380	0.00380	0.00377	0.00378	0.00378	0.00377	0.00378	0.00378	0.00392	0.00658	0.00884	0.00995	0.00378
VaR red.	-77.24%	-85.23%	-85.30%	-85.43%	-85.45%	-85.45%	-85.55%	-85.55%	-85.55%	-85.55%	-85.54%	-85.55%	-84.98%	-74.83%	-66.18%	-61.94%	-85.55%
VaR, perc.	0.00473	0.00177	0.00166	0.00151	0.00149	0.00149	0.00150	0.00149	0.00149	0.00152	0.00154	0.00148	0.00181	0.00539	0.00762	0.00889	0.00148
VaR, perc., red.	-82.10%	-93.29%	-93.72%	-94.27%	-94.35%	-94.37%	-94.31%	-94.35%	-94.36%	-94.25%	-94.17%	-94.39%	-93.14%	-79.60%	-71.17%	-66.37%	-94.40%
Δ skewness	-0.2067	0.0370	0.0466	0.0653	0.0689	0.0693	0.1203	0.1216	0.1222	0.1176	0.0975	0.1235	0.0130	-0.2265	-0.2320	-0.2131	-0.2131
Δ kurtosis	27.611	40.962	41.037	41.116	41.121	41.121	40.849	40.833	40.826	40.879	41.049	40.810	40.671	23.797	12.733	8.912	8.912
out-of sample,weekly																	
M. revenues	0.00000	0.00004	0.00004	0.00004	0.00004	0.00004	0.00005	0.00005	0.00005	0.00005	0.00005	0.00005	0.00004	-0.00002	-0.00004	-0.00001	0.00005
Variance	0.00004	0.00003	0.00003	0.00003	0.00003	0.00003	0.00003	0.00003	0.00003	0.00003	0.00003	0.00003	0.00003	0.00003	0.00004	0.00004	0.00003
Variance red.	-86.78%	-90.29%	-90.31%	-90.32%	-90.29%	-90.23%	-90.33%	-90.33%	-90.33%	-90.32%	-90.30%	-90.33%	-90.19%	-88.24%	-85.70%	-83.72%	-90.33%
VaR	0.00679	0.00386	0.00385	0.00382	0.00382	0.00382	0.00378	0.00378	0.00378	0.00378	0.00379	0.00378	0.00391	0.00567	0.00737	0.00844	0.00377
VaR red.	-74.01%	-85.22%	-85.28%	-85.37%	-85.38%	-85.37%	-85.55%	-85.55%	-85.54%	-85.54%	-85.49%	-85.55%	-85.04%	-78.32%	-71.78%	-67.71%	-85.56%
VaR, perc.	0.00611	0.00169	0.00164	0.00156	0.00155	0.00153	0.00148	0.00147	0.00146	0.00145	0.00144	0.00146	0.00182	0.00481	0.00690	0.00809	0.00151
VaR, perc., red.	-76.88%	-93.60%	-93.78%	-94.10%	-94.14%	-94.19%	-94.42%	-94.44%	-94.48%	-94.51%	-94.54%	-94.46%	-93.13%	-81.80%	-73.87%	-69.39%	-94.28%
Δ skewness	0.1107	0.0967	0.0956	0.1038	0.1171	0.1348	0.1244	0.1252	0.1268	0.1280	0.1277	0.1257	0.1151	0.0789	0.0627	0.0537	0.1273
Δ kurtosis	21.104	40.445	40.572	40.676	40.571	40.384	40.796	40.789	40.772	40.748	40.678	40.784	39.935	28.130	19.303	15.126	40.789

Table A.23: Corn Overview I

Corn	No	Naive	OLS,si	OLS,sp	ECM,si	ECM,sp	GARCH,si	GARCH,sp	bGARCH,si	bGARCH,sp	bGARCH,si,a	bGARCH,sp,a
in-sample												
M. revenues	0.00071	0.00056	0.00057	0.00056	0.00057	0.00056	0.00055	0.00055	0.00057	0.00057	0.00057	0.00056
Variance	0.00064	0.00016	0.00016	0.00016	0.00016	0.00016	0.00016	0.00016	0.00017	0.00016	0.00016	0.00016
Variance red.	-	-75.44%	-75.52%	-75.52%	-75.52%	-75.51%	-74.43%	-74.48%	-74.32%	-74.92%	-75.51%	-75.52%
VaR	0.04238	0.01650	0.01668	0.01665	0.01667	0.01662	0.01657	0.01655	0.01912	0.01767	0.01678	0.01663
VaR red.	-	-61.07%	-60.64%	-60.71%	-60.66%	-60.79%	-60.91%	-60.95%	-54.90%	-58.32%	-60.40%	-60.77%
VaR, perc.	0.03969	0.01088	0.01073	0.01074	0.01073	0.01076	0.00884	0.00888	0.01085	0.01097	0.01096	0.01076
VaR, perc., red.	-	-72.58%	-72.98%	-72.93%	-72.96%	-72.88%	-77.73%	-77.62%	-72.67%	-72.37%	-72.38%	-72.89%
Δ skewness	-	-0.2663	-0.2655	-0.2657	-0.2655	-0.2660	-0.2537	-0.2544	-0.6340	-0.3102	-0.2643	-0.2659
Δ kurtosis	-	21.329	20.512	20.624	20.546	20.762	22.218	22.222	17.400	18.039	20.110	20.732
out-of sample, daily												
M. revenues	-0.00033	-0.00023	-0.00024	-0.00024	-0.00024	-0.00024	-0.00021	-0.00023	-0.00018	-0.00016	-	-
Variance	0.00036	0.00009	0.00009	0.00009	0.00009	0.00009	0.00010	0.00010	0.00009	0.00009	-	-
Variance red.	-	-74.71%	-75.62%	-75.54%	-75.62%	-75.50%	-73.32%	-73.15%	-74.71%	-75.20%	-	-
VaR	0.03149	0.00881	0.00901	0.00897	0.00899	0.00888	0.00805	0.00836	0.01076	0.01068	-	-
VaR red.	-	-72.03%	-71.40%	-71.51%	-71.45%	-71.79%	-74.43%	-73.45%	-65.83%	-66.10%	-	-
VaR, perc.	0.03142	0.01075	0.00953	0.00972	0.00951	0.00954	0.01087	0.01078	0.01117	0.01111	-	-
VaR, perc., red.	-	-65.80%	-69.67%	-69.07%	-69.73%	-69.65%	-65.41%	-65.70%	-64.45%	-64.63%	-	-
Δ skewness	-	0.2549	0.3079	0.3332	0.3092	0.3247	0.4242	0.3777	0.1960	0.2630	-	-
Δ kurtosis	-	32.866	30.200	30.097	30.280	30.724	35.436	34.691	23.568	22.517	-	-
out-of sample, constant												
M. revenues	-0.00033	-0.00023	-0.00023	-0.00023	-0.00023	-0.00023	-0.00022	-0.00022	-0.00024	-0.00024	-0.00024	-0.00023
Variance	0.00036	0.00009	0.00009	0.00009	0.00009	0.00009	0.00010	0.00010	0.00009	0.00009	0.00009	0.00009
Variance red.	-	-74.71%	-75.47%	-75.39%	-75.44%	-75.28%	-71.58%	-71.70%	-75.58%	-76.28%	-75.72%	-75.30%
VaR	0.03149	0.00881	0.00899	0.00896	0.00898	0.00893	0.00887	0.00885	0.00904	0.00951	0.00910	0.00894
VaR red.	-	-72.03%	-71.44%	-71.53%	-71.47%	-71.64%	-71.84%	-71.89%	-71.30%	-69.80%	-71.10%	-71.62%
VaR, perc.	0.03142	0.01075	0.01045	0.01052	0.01047	0.01059	0.01124	0.01124	0.01035	0.00963	0.01022	0.01059
VaR, perc., red.	-	-65.80%	-66.74%	-66.52%	-66.67%	-66.28%	-64.22%	-64.24%	-67.05%	-69.36%	-67.46%	-66.30%
Δ skewness	-	0.2549	0.2549	0.2200	0.2242	0.2213	0.2296	0.3494	0.3466	0.2139	0.1668	0.2060
Δ kurtosis	-	32.866	32.866	31.681	31.850	31.734	32.056	33.804	33.823	31.423	28.873	31.064
out-of sample,weekly												
M. revenues	-0.00033	-0.00023	-0.00024	-0.00024	-0.00024	-0.00024	-0.00021	-0.00022	-0.00014	-0.00019	-	-
Variance	0.00036	0.00009	0.00009	0.00009	0.00009	0.00009	0.00010	0.00010	0.00008	0.00008	-	-
Variance red.	-	-74.71%	-75.69%	-75.60%	-75.68%	-75.55%	-73.28%	-73.06%	-76.80%	-76.58%	-	-
VaR	0.03149	0.00881	0.00899	0.00893	0.00898	0.00884	0.00805	0.00818	0.01091	0.01117	-	-
VaR red.	-	-72.03%	-71.47%	-71.63%	-71.49%	-71.92%	-74.42%	-74.03%	-65.37%	-64.53%	-	-
VaR, perc.	0.03142	0.01075	0.00953	0.00972	0.00952	0.00955	0.01086	0.01086	0.01118	0.01112	-	-
VaR, perc., red.	-	-65.80%	-69.65%	-69.07%	-69.71%	-69.62%	-65.42%	-65.43%	-64.43%	-64.59%	-	-
Δ skewness	-	0.2549	0.3195	0.3498	0.3174	0.3419	0.4157	0.4154	-0.0488	-0.0318	-	-
Δ kurtosis	-	32.866	30.086	30.008	30.151	30.649	35.580	35.125	23.752	22.361	-	-

Table A.24: Corn Overview II

Corn	Sharpe	Gini 1.5	Gini 2	Gini 5	Gini 10	Gini 20	Gini2 1.5	Gini2 2	Gini2 5	Gini2 10	Gini2 20	GSV 1	GSV 2	GSV 3	GSV 4	GSV 5	VaR
in-sample																	
M. revenues	-	0.00057	0.00057	0.00056	0.00056	0.00056	0.00055	0.00055	0.00055	0.00055	0.00056	0.00055	0.00056	0.00059	0.00061	0.00061	0.00056
Variance	-	0.00016	0.00016	0.00016	0.00016	0.00016	0.00016	0.00016	0.00016	0.00016	0.00016	0.00016	0.00016	0.00017	0.00020	0.00021	0.00016
Variance red.	-	-75.52%	-75.52%	-75.52%	-75.51%	-75.50%	-75.06%	-75.00%	-74.94%	-74.98%	-75.21%	-74.97%	-75.51%	-73.30%	-69.68%	-67.18%	-75.15%
VaR	-	0.01672	0.01667	0.01662	0.01661	0.01657	0.01643	0.01644	0.01645	0.01644	0.01643	0.01644	0.01661	0.01915	0.02153	0.02287	0.01643
VaR red.	-	-60.55%	-60.67%	-60.78%	-60.82%	-60.91%	-61.23%	-61.21%	-61.20%	-61.21%	-61.24%	-61.21%	-60.81%	-54.82%	-49.21%	-46.04%	-61.24%
VaR, perc.	-	0.01076	0.01073	0.01076	0.01077	0.01079	0.00997	0.00991	0.00973	0.00988	0.01034	0.00983	0.01077	0.01493	0.01739	0.01870	0.01016
VaR, perc., red.	-	-72.88%	-72.96%	-72.89%	-72.86%	-72.81%	-74.89%	-75.02%	-75.47%	-75.12%	-73.95%	-75.23%	-72.86%	-62.39%	-56.18%	-52.89%	-74.40%
Δ skewness	-	-0.2650	-0.2656	-0.2660	-0.2661	-0.2663	-0.2624	-0.2616	-0.2609	-0.2614	-0.2643	-0.2612	-0.2661	-0.2210	-0.1762	-0.1535	-0.2636
Δ kurtosis	-	20.350	20.551	20.750	20.821	20.993	22.056	22.100	22.132	22.109	21.888	22.117	20.811	13.387	8.802	6.892	21.964
out-of sample, daily																	
M. revenues	-	-0.00024	-0.00024	-0.00024	-0.00024	-0.00025	-0.00023	-0.00023	-0.00023	-0.00023	-0.00024	-0.00023	-0.00024	-0.00027	-0.00028	-0.00029	-0.00015
Variance	-	0.00009	0.00009	0.00009	0.00009	0.00009	0.00009	0.00010	0.00010	0.00009	0.00009	0.00010	0.00009	0.00010	0.00011	0.00012	0.00010
Variance red.	-	-75.93%	-75.85%	-75.70%	-75.65%	-75.56%	-73.88%	-73.71%	-73.70%	-74.01%	-74.74%	-73.50%	-75.48%	-73.42%	-69.52%	-66.87%	-73.43%
VaR	-	0.00910	0.00902	0.00900	0.00912	0.00937	0.00839	0.00836	0.00825	0.00812	0.00819	0.00841	0.00894	0.01322	0.01580	0.01704	0.00808
VaR red.	-	-71.10%	-71.37%	-71.42%	-71.05%	-70.26%	-73.36%	-73.45%	-73.80%	-74.21%	-73.99%	-73.28%	-71.62%	-58.02%	-49.84%	-45.89%	-74.35%
VaR, perc.	-	0.00946	0.00940	0.00958	0.00959	0.00980	0.01057	0.01058	0.01055	0.01039	0.00965	0.01063	0.00979	0.01256	0.01474	0.01604	0.01115
VaR, perc., red.	-	-69.89%	-70.09%	-69.50%	-69.47%	-68.80%	-66.36%	-66.32%	-66.43%	-66.92%	-69.28%	-66.16%	-68.84%	-60.01%	-53.08%	-48.93%	-64.50%
Δ skewness	-	0.2775	0.2772	0.2566	0.2360	0.2114	0.3423	0.3515	0.3751	0.4016	0.4305	0.3414	0.3249	0.0970	0.0081	-0.0249	0.4298
Δ kurtosis	-	29.837	30.365	30.899	30.630	29.742	34.476	34.619	34.843	34.871	33.500	34.662	30.457	13.905	7.395	5.264	35.147
out-of sample, constant																	
M. revenues	-	-0.00024	-0.00023	-0.00023	-0.00023	-0.00023	-0.00023	-0.00023	-0.00023	-0.00023	-0.00023	-0.00023	-0.00023	-0.00025	-0.00026	-0.00027	-0.00023
Variance	-	0.00009	0.00009	0.00009	0.00009	0.00009	0.00010	0.00010	0.00010	0.00010	0.00010	0.00010	0.00009	0.00009	0.00009	0.00010	0.00010
Variance red.	-	-75.58%	-75.44%	-75.29%	-75.23%	-75.07%	-73.25%	-73.07%	-72.91%	-73.03%	-73.76%	-72.99%	-75.24%	-76.20%	-73.81%	-71.75%	-73.56%
VaR	-	0.00904	0.00898	0.00893	0.00892	0.00888	0.00873	0.00874	0.00875	0.00874	0.00873	0.00874	0.00892	0.01157	0.01388	0.01510	0.00873
VaR red.	-	-71.31%	-71.47%	-71.63%	-71.69%	-71.81%	-72.27%	-72.25%	-72.22%	-72.24%	-72.27%	-72.24%	-71.68%	-63.26%	-55.91%	-52.06%	-72.28%
VaR, perc.	-	0.01036	0.01047	0.01059	0.01061	0.01065	0.01093	0.01088	0.01084	0.01087	0.01094	0.01086	0.01061	0.01106	0.01375	0.01434	0.01096
VaR, perc., red.	-	-67.04%	-66.66%	-66.29%	-66.24%	-66.10%	-65.22%	-65.36%	-65.49%	-65.39%	-65.17%	-65.43%	-66.24%	-64.80%	-56.22%	-54.36%	-65.12%
Δ skewness	-	0.1305	0.2142	0.2215	0.2292	0.2320	0.2392	0.3056	0.3110	0.3154	0.3121	0.2898	0.3132	0.2316	0.0704	0.0305	0.0231
Δ kurtosis	-	26.123	31.435	31.741	32.038	32.142	32.393	33.769	33.810	33.836	33.817	33.587	33.824	32.128	19.287	10.958	7.734
out-of sample,weekly																	
M. revenues	-	-0.00024	-0.00024	-0.00024	-0.00024	-0.00025	-0.00023	-0.00023	-0.00023	-0.00023	-0.00024	-0.00023	-0.00024	-0.00027	-0.00028	-0.00029	-0.00021
Variance	-	0.00009	0.00009	0.00009	0.00009	0.00009	0.00009	0.00010	0.00010	0.00009	0.00009	0.00010	0.00009	0.00010	0.00011	0.00012	0.00010
Variance red.	-	-75.87%	-75.79%	-75.62%	-75.54%	-75.39%	-73.86%	-73.70%	-73.69%	-73.99%	-74.69%	-73.50%	-75.43%	-73.36%	-69.46%	-66.82%	-73.64%
VaR	-	0.00903	0.00893	0.00885	0.00887	0.00895	0.00836	0.00834	0.00824	0.00811	0.00816	0.00842	0.00893	0.01325	0.01584	0.01707	0.00856
VaR red.	-	-71.31%	-71.64%	-71.91%	-71.85%	-71.57%	-73.45%	-73.50%	-73.83%	-74.25%	-74.10%	-73.28%	-71.64%	-57.92%	-49.71%	-45.78%	-72.83%
VaR, perc.	-	0.00948	0.00941	0.00958	0.00960	0.00981	0.01057	0.01059	0.01055	0.01041	0.00969	0.01063	0.00984	0.01257	0.01474	0.01604	0.01116
VaR, perc., red.	-	-69.82%	-70.06%	-69.49%	-69.46%	-68.78%	-66.35%	-66.31%	-66.41%	-66.87%	-69.16%	-66.15%	-68.66%	-59.98%	-53.07%	-48.93%	-64.48%
Δ skewness	-	0.2900	0.2949	0.2940	0.2990	0.3172	0.3488	0.3551	0.3766	0.4030	0.4346	0.3416	0.3204	0.0824	-0.0058	-0.0360	0.3099
Δ kurtosis	-	30.076	30.622	31.257	31.158	30.579	34.543	34.662	34.884	34.933	33.658	34.658	30.615	14.028	7.462	5.310	34.288

Table A.25: Oil Overview I

Oil	No	Naive	OLS,si	OLS,sp	ECM,si	ECM,sp	GARCH,si	GARCH,sp	bGARCH,si	bGARCH,sp	bGARCH,si,a	bGARCH,sp,a
in-sample												
M. revenues	0.00053	0.00057	0.00057	-	0.00057	-	0.00057	0.00057	0.00057	0.00057	0.00071	0.00076
Variance	0.00084	0.00014	0.00014	-	0.00014	-	0.00014	0.00014	0.00014	0.00014	0.00017	0.00015
Variance red.	-	-82.84%	-82.86%	-	-82.84%	-	-82.84%	-82.85%	-82.83%	-82.82%	-80.31%	-81.77%
VaR	0.04415	-0.02310	-0.02400	-	-0.02464	-	-0.02328	-0.02332	-0.02281	-0.02270	-0.03068	-0.02876
VaR red.		-152.32%	-154.35%	-	-155.81%	-	-152.73%	-152.82%	-151.67%	-151.42%	-169.49%	-165.15%
VaR, perc.	0.04369	0.00738	0.00729	-	0.00754	-	0.00743	0.00744	0.00731	0.00728	0.00825	0.00766
VaR, perc., red.	-	-83.12%	-83.31%	-	-82.75%	-	-82.99%	-82.96%	-83.27%	-83.33%	-81.11%	-82.48%
Δ skewness	-	4.5209	4.6037	-	4.6625	-	4.5375	4.5411	4.4941	4.4837	5.3176	5.1681
Δ kurtosis	-	86.956	88.807	-	90.082	-	87.331	87.411	86.348	86.113	91.088	91.663
out-of sample, daily												
M. revenues	-0.00002	0.00018	0.00018	-	0.00019	-	0.00018	0.00018	0.00019	0.00018	-	-
Variance	0.00030	0.00000	0.00000	-	0.00000	-	0.00000	0.00000	0.00001	0.00001	-	-
Variance red.	-	-98.72%	-98.68%	-	-98.64%	-	-98.71%	-98.71%	-98.33%	-98.33%	-	-
VaR	0.02919	0.00238	0.00248	-	0.00260	-	0.00239	0.00240	0.00299	0.00301	-	-
VaR red.		-91.86%	-91.50%	-	-91.08%	-	-91.80%	-91.78%	-89.74%	-89.68%	-	-
VaR, perc.	0.02637	0.00192	0.00188	-	0.00188	-	0.00192	0.00192	0.00306	0.00294	-	-
VaR, perc., red.	-	-92.72%	-92.85%	-	-92.85%	-	-92.72%	-92.73%	-88.39%	-88.86%	-	-
Δ skewness	-	0.1631	0.0124	-	-0.1284	-	0.1461	0.1400	0.5167	0.4780	-	-
Δ kurtosis		20.983	21.393	-	21.366	-	20.968	20.960	9.843	9.958	-	-
out-of sample, constant												
M. revenues	-0.00002	0.00018	0.00018	-	0.00019	-	0.00018	0.00018	0.00018	0.00018	0.00018	0.00019
Variance	0.00030	0.00000	0.00000	-	0.00000	-	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
Variance red.	-	-98.72%	-98.68%	-	-98.60%	-	-98.72%	-98.72%	-98.73%	-98.73%	-98.73%	-98.62%
VaR	0.02919	0.00238	0.00250	-	0.00266	-	0.00239	0.00240	0.00236	0.00235	0.00235	0.00264
VaR red.		-91.86%	-91.43%	-	-90.88%	-	-91.80%	-91.78%	-91.92%	-91.94%	-91.96%	-90.96%
VaR, perc.	0.02637	0.00192	0.00189	-	0.00195	-	0.00192	0.00192	0.00193	0.00193	0.00197	0.00193
VaR, perc., red.	-	-92.72%	-92.82%	-	-92.62%	-	-92.73%	-92.74%	-92.70%	-92.69%	-92.52%	-92.68%
Δ skewness	-	0.1631	0.1631	-	0.1457	-	0.1370	0.1283	0.1208	0.2187	0.2398	0.2800
Δ kurtosis		20.983	20.983	-	21.0747	-	21.1205	21.166	21.199	20.588	20.406	20.012
out-of sample,weekly												
M. revenues	-0.00002	0.00018	0.00018	-	0.00019	-	0.00018	0.00018	0.00019	0.00018	-	-
Variance	0.00030	0.00000	0.00000	-	0.00000	-	0.00000	0.00000	0.00000	0.00000	-	-
Variance red.	-	-98.72%	-98.68%	-	-98.64%	-	-98.71%	-98.71%	-98.41%	-98.42%	-	-
VaR	0.02919	0.00238	0.00248	-	0.00260	-	0.00239	0.00240	0.00292	0.00292	-	-
VaR red.	-	-91.86%	-91.50%	-	-91.08%	-	-91.80%	-91.78%	-89.99%	-90.01%	-	-
VaR, perc.	0.02637	0.00192	0.00188	-	0.00188	-	0.00192	0.00192	0.00298	0.00288	-	-
VaR, perc., red.	-	-92.72%	-92.85%	-	-92.85%	-	-92.72%	-92.73%	-88.69%	-89.06%	-	-
Δ skewness	-	0.1631	0.0070	-	-0.1350	-	0.1349	0.1315	0.4540	0.4386	-	-
Δ kurtosis	-	20.983	21.464	-	21.440	-	21.109	21.084	10.760	10.922	-	-

Table A.26: Oil Overview II

Oil	Sharpe	Gini 1.5	Gini 2	Gini 5	Gini 10	Gini 20	Gini2 1.5	Gini2 2	Gini2 5	Gini2 10	Gini2 20	GSV 1	GSV 2	GSV 3	GSV 4	GSV 5	VaR
in-sample																	
M. revenues	0.00057	0.00057	0.00057	0.00057	0.00057	0.00057	0.00057	0.00057	0.00057	0.00057	0.00057	0.00057	0.00057	0.00057	0.00057	0.00057	0.00058
Variance	0.00014	0.00014	0.00014	0.00014	0.00015	0.00015	0.00014	0.00014	0.00014	0.00014	0.00014	0.00014	0.00014	0.00014	0.00015	0.00015	0.00015
Variance red.	-82.81%	-82.84%	-82.86%	-82.83%	-82.76%	-82.64%	-82.86%	-82.86%	-82.85%	-82.84%	-82.79%	-82.85%	-82.81%	-82.81%	-82.57%	-82.76%	-82.21%
VaR	0.00969	0.00958	0.00947	0.00925	0.00907	0.00884	0.00942	0.00943	0.00951	0.00960	0.00971	0.00937	0.00968	0.00968	0.00994	0.00907	-0.02651
VaR red.	1566.85%	1548.04%	1528.95%	1490.44%	1459.55%	1419.85%	1521.27%	1522.53%	1536.08%	1551.40%	1570.97%	1512.70%	1564.41%	1564.41%	1609.17%	1459.60%	-160.04%
VaR, perc.	0.00749	0.00754	0.00733	0.00731	0.00756	0.00793	0.00733	0.00731	0.00748	0.00752	0.00745	0.00745	0.00752	0.00752	0.00753	0.00756	0.00782
VaR, perc., red.	-82.85%	-82.75%	-83.23%	-83.28%	-82.70%	-81.86%	-83.23%	-83.27%	-82.87%	-82.78%	-82.95%	-82.94%	-82.79%	-82.79%	-82.76%	-82.70%	-82.09%
Δ skewness	4.7114	4.6621	4.6084	4.4924	4.3942	4.2635	4.5860	4.5897	4.6288	4.6712	4.7217	4.5605	4.7053	4.7053	4.7996	4.3944	4.8135
Δ kurtosis	91.100	90.073	88.909	86.310	84.060	81.030	88.415	88.496	89.356	90.266	91.305	87.847	90.975	90.975	92.632	84.064	92.332
out-of sample, daily																	
M. revenues	0.00028	0.00019	0.00019	0.00018	0.00017	0.00016	0.00019	0.00019	0.00019	0.00019	0.00020	0.00019	0.00020	0.00020	0.00017	0.00010	0.00023
Variance	0.00002	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00001	0.00001	0.00001
Variance red.	-94.79%	-98.64%	-98.68%	-98.72%	-98.70%	-98.62%	-98.70%	-98.70%	-98.68%	-98.64%	-98.56%	-98.71%	-98.58%	-98.58%	-98.09%	-97.87%	-97.78%
VaR	0.00648	0.00261	0.00249	0.00236	0.00236	0.00246	0.00245	0.00245	0.00252	0.00262	0.00278	0.00242	0.00275	0.00275	0.00358	0.00372	0.00394
VaR red.	-77.81%	-91.07%	-91.48%	-91.91%	-91.92%	-91.58%	-91.61%	-91.60%	-91.37%	-91.03%	-90.46%	-91.72%	-90.59%	-90.59%	-87.74%	-87.26%	-86.51%
VaR, perc.	0.00491	0.00191	0.00188	0.00192	0.00200	0.00224	0.00191	0.00191	0.00188	0.00189	0.00202	0.00191	0.00199	0.00199	0.00304	0.00319	0.00308
VaR, perc., red.	-81.39%	-92.76%	-92.89%	-92.73%	-92.42%	-91.51%	-92.76%	-92.77%	-92.88%	-92.81%	-92.36%	-92.77%	-92.45%	-92.45%	-88.46%	-87.90%	-88.33%
Δ skewness	-0.4005	-0.1180	0.0049	0.2707	0.4668	0.6585	0.0285	0.0177	-0.0738	-0.1656	-0.2526	0.0832	-0.2259	-0.2259	-0.2352	0.1864	-0.3443
Δ kurtosis	7.545	21.118	21.308	20.018	17.750	14.089	21.532	21.594	21.733	21.444	20.429	21.361	20.505	20.505	12.542	7.953	12.319
out-of sample, constant																	
M. revenues	0.00019	0.00019	0.00019	0.00018	0.00018	0.00017	0.00018	0.00018	0.00019	0.00019	0.00019	0.00018	0.00019	0.00019	0.00020	0.00018	0.00020
Variance	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00001	0.00000	0.00001
Variance red.	-98.50%	-98.61%	-98.67%	-98.73%	-98.71%	-98.64%	-98.69%	-98.69%	-98.65%	-98.59%	-98.47%	-98.71%	-98.52%	-98.52%	-98.04%	-98.71%	-97.47%
VaR	0.00286	0.00266	0.00251	0.00236	0.00235	0.00247	0.00247	0.00247	0.00256	0.00269	0.00291	0.00242	0.00283	0.00283	0.00357	0.00235	0.00422
VaR red.	-90.19%	-90.89%	-91.40%	-91.92%	-91.94%	-91.54%	-91.56%	-91.53%	-91.23%	-90.78%	-90.02%	-91.70%	-90.30%	-90.30%	-87.76%	-91.94%	-85.54%
VaR, perc.	0.00214	0.00195	0.00190	0.00193	0.00202	0.00218	0.00191	0.00190	0.00190	0.00197	0.00215	0.00191	0.00214	0.00214	0.00284	0.00202	0.00304
VaR, perc., red.	-91.88%	-92.62%	-92.79%	-92.70%	-92.34%	-91.73%	-92.77%	-92.78%	-92.80%	-92.53%	-91.84%	-92.76%	-91.90%	-91.90%	-89.24%	-92.34%	-88.48%
Δ skewness	-0.1069	-0.1909	-0.1184	-0.0184	0.2221	0.4093	0.5971	0.0270	0.0194	-0.0582	-0.1335	-0.2024	0.0799	-0.1833	-0.1833	-0.2144	0.4090
Δ kurtosis	20.681	19.029	20.540	21.299	20.560	18.317	14.462	21.382	21.377	21.108	20.325	18.602	21.332	19.266	19.266	13.285	18.321
out-of sample,weekly																	
M. revenues	0.00025	0.00019	0.00019	0.00018	0.00017	0.00017	0.00019	0.00019	0.00019	0.00019	0.00020	0.00019	0.00020	0.00020	0.00017	0.00011	0.00023
Variance	0.00002	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00001	0.00001	0.00001
Variance red.	-94.75%	-98.63%	-98.68%	-98.72%	-98.70%	-98.63%	-98.70%	-98.70%	-98.68%	-98.63%	-98.55%	-98.71%	-98.58%	-98.58%	-98.08%	-97.87%	-97.80%
VaR	0.00662	0.00261	0.00249	0.00236	0.00236	0.00246	0.00245	0.00246	0.00252	0.00262	0.00279	0.00242	0.00276	0.00276	0.00360	0.00372	0.00391
VaR red.	-77.32%	-91.05%	-91.46%	-91.91%	-91.92%	-91.59%	-91.60%	-91.59%	-91.36%	-91.01%	-90.43%	-91.71%	-90.56%	-90.56%	-87.68%	-87.25%	-86.61%
VaR, perc.	0.00507	0.00191	0.00188	0.00192	0.00199	0.00224	0.00191	0.00191	0.00188	0.00190	0.00201	0.00191	0.00199	0.00199	0.00304	0.00315	0.00287
VaR, perc., red.	-80.78%	-92.76%	-92.88%	-92.73%	-92.44%	-91.51%	-92.76%	-92.76%	-92.88%	-92.81%	-92.36%	-92.77%	-92.44%	-92.44%	-88.45%	-88.05%	-89.10%
Δ skewness	-0.6638	-0.1362	-0.0091	0.2635	0.4616	0.6553	0.0216	0.0119	-0.0815	-0.1793	-0.2827	0.0748	-0.2529	-0.2529	-0.2726	0.1939	-0.3451
Δ kurtosis	9.391	21.296	21.447	20.100	17.831	14.176	21.594	21.646	21.805	21.568	20.701	21.411	20.731	20.731	12.886	7.910	12.665

Table A.27: Platinum Overview I

Platinum	No	Naive	OLS,si	OLS,sp	ECM,si	ECM,sp	GARCH,si	GARCH,sp	bGARCH,si	bGARCH,sp	bGARCH,si,a	bGARCH,sp,a
in-sample												
M. revenues	0.00029	0.00006	0.00013	0.00014	0.00013	0.00014	0.00013	0.00014	0.00001	0.00004	0.00013	0.00013
Variance	0.00032	0.00018	0.00015	0.00015	0.00015	0.00015	0.00015	0.00015	0.00015	0.00015	0.00015	0.00015
Variance red.	-	-43.41%	-53.45%	-53.39%	-53.45%	-53.43%	-53.44%	-53.43%	-51.51%	-51.72%	-53.45%	-53.45%
VaR	0.03091	0.01941	0.01715	0.01722	0.01714	0.01719	0.01716	0.01719	0.01872	0.01863	0.01714	0.01714
VaR red.	-	-37.21%	-44.53%	-44.30%	-44.54%	-44.39%	-44.47%	-44.40%	-39.45%	-39.74%	-44.56%	-44.56%
VaR, perc.	0.02976	0.02058	0.01837	0.01829	0.01831	0.01830	0.01865	0.01830	0.01969	0.01922	0.01831	0.01831
VaR, perc., red.	-	-30.86%	-38.29%	-38.55%	-38.47%	-38.51%	-37.33%	-38.51%	-33.86%	-35.44%	-38.47%	-38.47%
Δ skewness	-	0.7322	0.6835	0.6703	0.6841	0.6752	0.6796	0.6755	0.4967	0.5018	0.6858	0.6855
Δ kurtosis	-	4.432	6.983	6.915	6.986	6.944	6.967	6.946	4.693	4.825	6.991	6.990
out-of sample, daily												
M. revenues	-0.00022	0.00003	-0.00004	-0.00005	-0.00004	-0.00005	-0.00004	-0.00004	-0.00012	-0.00012	-	-
Variance	0.00014	0.00009	0.00006	0.00006	0.00006	0.00006	0.00006	0.00006	0.00006	0.00006	-	-
Variance red.	-	-38.74%	-54.46%	-54.61%	-54.41%	-54.58%	-54.24%	-54.47%	-53.46%	-53.58%	-	-
VaR	0.01995	0.01524	0.01332	0.01330	0.01333	0.01331	0.01335	0.01332	0.01347	0.01344	-	-
VaR red.	-	-23.63%	-33.25%	-33.33%	-33.21%	-33.31%	-33.10%	-33.25%	-32.50%	-32.65%	-	-
VaR, perc.	0.01996	0.01458	0.01411	0.01415	0.01408	0.01408	0.01401	0.01409	0.01457	0.01429	-	-
VaR, perc., red.	-	-26.98%	-29.33%	-29.12%	-29.47%	-29.47%	-29.81%	-29.42%	-27.01%	-28.42%	-	-
Δ skewness	-	0.2016	0.1074	0.1052	0.1072	0.1049	0.1092	0.1070	0.1022	0.1071	-	-
Δ kurtosis		-0.740	-0.562	-0.565	-0.566	-0.566	-0.571	-0.564	-0.516	-0.506	-	-
out-of sample, constant												
M. revenues	-0.00022	0.00003	-0.00004	-0.00005	-0.00004	-0.00005	-0.00005	-0.00005	-0.00004	-0.00004	-0.00004	-0.00004
Variance	0.00014	0.00009	0.00006	0.00006	0.00006	0.00006	0.00006	0.00006	0.00006	0.00006	0.00006	0.00006
Variance red.	-	-38.74%	-54.27%	-54.48%	-54.25%	-54.42%	-54.35%	-54.42%	-54.26%	-54.19%	-54.21%	-54.22%
VaR	0.01995	0.01524	0.01335	0.01332	0.01335	0.01333	0.01334	0.01333	0.01335	0.01336	0.01336	0.01336
VaR red.	-	-23.63%	-33.08%	-33.23%	-33.07%	-33.19%	-33.14%	-33.18%	-33.08%	-33.03%	-33.04%	-33.05%
VaR, perc.	0.01996	0.01458	0.01403	0.01405	0.01402	0.01416	0.01409	0.01416	0.01402	0.01400	0.01400	0.01400
VaR, perc., red.	-	-26.98%	-29.74%	-29.62%	-29.80%	-29.09%	-29.42%	-29.10%	-29.76%	-29.87%	-29.89%	-29.89%
Δ skewness	-	0.2016	0.2016	0.1066	0.1054	0.1067	0.1057	0.1061	0.1058	0.1066	0.1070	0.1069
Δ kurtosis		-0.740	-0.740	-0.584	-0.582	-0.584	-0.583	-0.583	-0.583	-0.584	-0.585	-0.584
out-of sample,weekly												
M. revenues	-0.00022	0.00003	-0.00004	-0.00005	-0.00004	-0.00005	-0.00004	-0.00004	-0.00011	-0.00011	-	-
Variance	0.00014	0.00009	0.00006	0.00006	0.00006	0.00006	0.00006	0.00006	0.00006	0.00006	-	-
Variance red.	-	-38.74%	-54.50%	-54.64%	-54.44%	-54.61%	-54.29%	-54.51%	-54.48%	-54.63%	-	-
VaR	0.01995	0.01524	0.01331	0.01330	0.01332	0.01330	0.01334	0.01331	0.01335	0.01333	-	-
VaR red.	-	-23.63%	-33.27%	-33.35%	-33.22%	-33.32%	-33.13%	-33.27%	-33.07%	-33.20%	-	-
VaR, perc.	0.01996	0.01458	0.01410	0.01415	0.01408	0.01408	0.01402	0.01408	0.01420	0.01440	-	-
VaR, perc., red.	-	-26.98%	-29.36%	-29.12%	-29.50%	-29.49%	-29.80%	-29.45%	-28.86%	-27.85%	-	-
Δ skewness	-	0.2016	0.1065	0.1047	0.1067	0.1043	0.1084	0.1064	0.0866	0.0879	-	-
Δ kurtosis	-	-0.740	-0.562	-0.565	-0.567	-0.566	-0.570	-0.563	-0.520	-0.508	-	-

Table A.28: Platinum Overview II

Platinum	Sharpe	Gini 1.5	Gini 2	Gini 5	Gini 10	Gini 20	Gini2 1.5	Gini2 2	Gini2 5	Gini2 10	Gini2 20	GSV 1	GSV 2	GSV 3	GSV 4	GSV 5	VaR
in-sample																	
M. revenues	-	0.00014	0.00013	0.00013	0.00012	0.00012	0.00013	0.00013	0.00013	0.00012	0.00012	0.00013	0.00013	0.00013	0.00014	0.00015	0.00013
Variance	-	0.00015	0.00015	0.00015	0.00015	0.00015	0.00015	0.00015	0.00015	0.00015	0.00015	0.00015	0.00015	0.00015	0.00015	0.00015	0.00015
Variance red.	-	-53.41%	-53.44%	-53.43%	-53.25%	-52.92%	-53.45%	-53.45%	-53.38%	-53.28%	-53.18%	-53.45%	-53.40%	-53.43%	-53.37%	-52.52%	-53.34%
VaR	-	0.01721	0.01717	0.01712	0.01711	0.01716	0.01715	0.01713	0.01711	0.01711	0.01712	0.01715	0.01711	0.01712	0.01723	0.01767	0.01711
VaR red.	-	-44.33%	-44.44%	-44.61%	-44.63%	-44.48%	-44.51%	-44.57%	-44.64%	-44.64%	-44.61%	-44.52%	-44.64%	-44.61%	-44.24%	-42.83%	-44.65%
VaR, perc.	-	0.01837	0.01856	0.01832	0.01834	0.01834	0.01860	0.01831	0.01840	0.01839	0.01831	0.01845	0.01842	0.01831	0.01827	0.01823	0.01852
VaR, perc., red.	-	-38.29%	-37.65%	-38.46%	-38.39%	-38.40%	-37.50%	-38.47%	-38.18%	-38.21%	-38.48%	-38.03%	-38.11%	-38.47%	-38.63%	-38.74%	-37.78%
Δ skewness	-	0.6719	0.6778	0.6903	0.7027	0.7118	0.6818	0.6867	0.6959	0.7015	0.7053	0.6829	0.6941	0.6900	0.6678	0.6189	0.6983
Δ kurtosis	-	6.925	6.958	7.002	6.990	6.912	6.977	6.994	7.006	6.994	6.975	6.981	7.006	7.002	6.898	6.449	7.003
out-of sample, daily																	
M. revenues	-	-0.00005	-0.00004	-0.00004	-0.00003	-0.00003	-0.00004	-0.00004	-0.00004	-0.00004	-0.00004	-0.00003	-0.00004	-0.00004	-0.00004	-0.00005	-0.00003
Variance	-	0.00006	0.00006	0.00006	0.00006	0.00006	0.00006	0.00006	0.00006	0.00006	0.00006	0.00006	0.00006	0.00006	0.00006	0.00006	0.00006
Variance red.	-	-54.64%	-54.62%	-54.48%	-54.17%	-53.66%	-54.55%	-54.50%	-54.36%	-54.22%	-54.16%	-54.52%	-54.39%	-54.38%	-54.27%	-53.34%	-54.24%
VaR	-	0.01329	0.01330	0.01332	0.01336	0.01343	0.01331	0.01331	0.01333	0.01335	0.01336	0.01331	0.01333	0.01332	0.01332	0.01344	0.01335
VaR red.	-	-33.38%	-33.35%	-33.24%	-33.03%	-32.69%	-33.30%	-33.28%	-33.19%	-33.10%	-33.05%	-33.28%	-33.20%	-33.22%	-33.22%	-32.65%	-33.11%
VaR, perc.	-	0.01389	0.01401	0.01409	0.01388	0.01395	0.01409	0.01404	0.01406	0.01392	0.01384	0.01414	0.01414	0.01410	0.01400	0.01415	0.01402
VaR, perc., red.	-	-30.45%	-29.83%	-29.42%	-30.50%	-30.14%	-29.43%	-29.69%	-29.57%	-30.28%	-30.70%	-29.20%	-29.17%	-29.38%	-29.87%	-29.14%	-29.76%
Δ skewness	-	0.1066	0.1059	0.1050	0.1061	0.1086	0.1062	0.1067	0.1085	0.1092	0.1089	0.1050	0.1068	0.1098	0.1181	0.1295	0.1088
Δ kurtosis	-	-0.563	-0.561	-0.556	-0.550	-0.550	-0.560	-0.559	-0.559	-0.560	-0.554	-0.545	-0.553	-0.555	-0.570	-0.605	-0.562
out-of sample, constant																	
M. revenues	-	-0.00005	-0.00005	-0.00004	-0.00003	-0.00003	-0.00004	-0.00004	-0.00004	-0.00003	-0.00003	-0.00004	-0.00004	-0.00004	-0.00005	-0.00007	-0.00004
Variance	-	0.00006	0.00006	0.00006	0.00006	0.00007	0.00006	0.00006	0.00006	0.00006	0.00006	0.00006	0.00006	0.00006	0.00006	0.00006	0.00006
Variance red.	-	-54.47%	-54.38%	-54.08%	-53.52%	-52.79%	-54.31%	-54.19%	-53.87%	-53.59%	-53.34%	-54.28%	-53.94%	-54.09%	-54.51%	-54.31%	-53.76%
VaR	-	0.01332	0.01334	0.01338	0.01345	0.01355	0.01335	0.01336	0.01340	0.01344	0.01347	0.01335	0.01339	0.01337	0.01332	0.01335	0.01342
VaR red.	-	-33.22%	-33.16%	-32.95%	-32.58%	-32.09%	-33.11%	-33.03%	-32.81%	-32.62%	-32.46%	-33.09%	-32.86%	-32.96%	-33.24%	-33.10%	-32.74%
VaR, perc.	-	0.01411	0.01412	0.01404	0.01402	0.01400	0.01405	0.01400	0.01391	0.01397	0.01412	0.01404	0.01404	0.01403	0.01393	0.01453	0.01390
VaR, perc., red.	-	-29.33%	-29.28%	-29.70%	-29.79%	-29.86%	-29.60%	-29.87%	-30.31%	-30.04%	-29.28%	-29.70%	-29.68%	-29.73%	-30.21%	-27.23%	-30.38%
Δ skewness	-	0.1062	0.1055	0.1060	0.1076	0.1107	0.1149	0.1064	0.1070	0.1088	0.1103	0.1117	0.1065	0.1084	0.1076	0.1052	0.1047
Δ kurtosis	-	-0.583	-0.582	-0.583	-0.585	-0.589	-0.595	-0.584	-0.585	-0.587	-0.589	-0.591	-0.584	-0.586	-0.585	-0.582	-0.574
out-of sample,weekly																	
M. revenues	-	-0.00005	-0.00004	-0.00004	-0.00003	-0.00002	-0.00004	-0.00004	-0.00004	-0.00004	-0.00004	-0.00003	-0.00004	-0.00005	-0.00005	-0.00006	-0.00003
Variance	-	0.00006	0.00006	0.00006	0.00006	0.00006	0.00006	0.00006	0.00006	0.00006	0.00006	0.00006	0.00006	0.00006	0.00006	0.00006	0.00006
Variance red.	-	-54.61%	-54.59%	-54.45%	-54.14%	-53.64%	-54.52%	-54.48%	-54.34%	-54.21%	-54.15%	-54.48%	-54.37%	-54.39%	-54.33%	-53.44%	-54.29%
VaR	-	0.01330	0.01330	0.01332	0.01337	0.01343	0.01331	0.01332	0.01334	0.01335	0.01336	0.01332	0.01333	0.01332	0.01332	0.01343	0.01335
VaR red.	-	-33.35%	-33.32%	-33.22%	-33.01%	-32.67%	-33.28%	-33.25%	-33.16%	-33.06%	-33.03%	-33.23%	-33.16%	-33.21%	-33.25%	-32.71%	-33.10%
VaR, perc.	-	0.01389	0.01410	0.01409	0.01388	0.01395	0.01409	0.01404	0.01407	0.01393	0.01384	0.01414	0.01415	0.01412	0.01401	0.01423	0.01402
VaR, perc., red.	-	-30.44%	-29.38%	-29.41%	-30.47%	-30.13%	-29.43%	-29.69%	-29.53%	-30.25%	-30.70%	-29.18%	-29.13%	-29.27%	-29.80%	-28.74%	-29.78%
Δ skewness	-	0.1063	0.1056	0.1049	0.1059	0.1080	0.1062	0.1063	0.1069	0.1073	0.1072	0.1030	0.1049	0.1084	0.1168	0.1276	0.1052
Δ kurtosis	-	-0.564	-0.563	-0.556	-0.552	-0.551	-0.562	-0.561	-0.561	-0.561	-0.555	-0.548	-0.554	-0.555	-0.566	-0.599	-0.559

Table A.29: Soybeans Overview I

Soybeans	No	Naive	OLS,si	OLS,sp	ECM,si	ECM,sp	GARCH,si	GARCH,sp	bGARCH,si	bGARCH,sp	bGARCH,si,a	bGARCH,sp,a
in-sample												
M. revenues	0.00061	-0.00019	-0.00018	-0.00018	-0.00018	-0.00018	-0.00019	-0.00018	-0.00014	-0.00014	-0.00017	-0.00017
Variance	0.00042	0.00005	0.00005	0.00005	0.00005	0.00005	0.00005	0.00005	0.00006	0.00006	0.00005	0.00005
Variance red.	-	-87.26%	-87.27%	-87.27%	-87.27%	-87.27%	-87.25%	-87.27%	-86.47%	-86.60%	-87.26%	-87.25%
VaR	0.03612	0.00516	0.00524	0.00520	0.00525	0.00521	0.00510	0.00521	0.00254	0.00253	0.00538	0.00539
VaR red.	-	-85.72%	-85.49%	-85.61%	-85.47%	-85.58%	-85.87%	-85.59%	-92.96%	-93.00%	-85.10%	-85.07%
VaR, perc.	0.03590	0.00695	0.00687	0.00684	0.00691	0.00682	0.00695	0.00683	0.00715	0.00700	0.00693	0.00694
VaR, perc., red.	-	-80.64%	-80.85%	-80.94%	-80.75%	-81.00%	-80.65%	-80.98%	-80.09%	-80.51%	-80.70%	-80.67%
Δ skewness	-	-0.5373	-0.5626	-0.5512	-0.5652	-0.5541	-0.5162	-0.5529	0.5056	0.4729	-0.5944	-0.5964
Δ kurtosis	-	59.305	59.031	59.173	58.994	59.139	59.430	59.153	64.245	64.702	58.466	58.420
out-of sample, daily												
M. revenues	0.00021	-0.00039	-0.00037	-0.00038	-0.00038	-0.00038	-0.00037	-0.00037	-0.00023	-0.00022	-	-
Variance	0.00022	0.00004	0.00004	0.00004	0.00004	0.00004	0.00004	0.00004	0.00004	0.00004	-	-
Variance red.	-	-83.74%	-83.70%	-83.71%	-83.70%	-83.71%	-83.58%	-83.66%	-83.62%	-83.53%	-	-
VaR	0.02478	0.00276	0.00288	0.00285	0.00288	0.00285	0.00293	0.00289	0.00287	0.00288	-	-
VaR red.	-	-88.86%	-88.37%	-88.49%	-88.38%	-88.50%	-88.18%	-88.35%	-88.40%	-88.37%	-	-
VaR, perc.	0.02277	0.00613	0.00654	0.00659	0.00651	0.00656	0.00669	0.00670	0.00669	0.00655	-	-
VaR, perc., red.	-	-73.10%	-71.30%	-71.08%	-71.42%	-71.19%	-70.64%	-70.59%	-70.61%	-71.22%	-	-
Δ skewness	-	-0.5791	-0.6111	-0.6048	-0.6091	-0.6032	-0.5852	-0.5977	-0.4911	-0.4749	-	-
Δ kurtosis	-	67.676	67.088	67.262	67.094	67.260	66.480	66.909	65.706	65.499	-	-
out-of sample, constant												
M. revenues	0.00021	-0.00039	-0.00039	-0.00039	-0.00039	-0.00039	-0.00040	-0.00039	-0.00040	-0.00040	-0.00038	-0.00038
Variance	0.00022	0.00004	0.00004	0.00004	0.00004	0.00004	0.00004	0.00004	0.00004	0.00004	0.00004	0.00004
Variance red.	-	-83.74%	-83.73%	-83.74%	-83.73%	-83.74%	-83.74%	-83.74%	-83.73%	-83.73%	-83.69%	-83.69%
VaR	0.02478	0.00276	0.00282	0.00279	0.00283	0.00280	0.00272	0.00280	0.00269	0.00269	0.00293	0.00294
VaR red.	-	-88.86%	-88.61%	-88.73%	-88.58%	-88.70%	-89.02%	-88.71%	-89.14%	-89.14%	-88.18%	-88.15%
VaR, perc.	0.02277	0.00613	0.00601	0.00604	0.00603	0.00602	0.00626	0.00603	0.00637	0.00637	0.00634	0.00637
VaR, perc., red.	-	-73.10%	-73.63%	-73.49%	-73.51%	-73.58%	-72.51%	-73.54%	-72.01%	-72.02%	-72.14%	-72.04%
Δ skewness	-	-0.5791	-0.5791	-0.5961	-0.5884	-0.5979	-0.5904	-0.5647	-0.5896	-0.5517	-0.5520	-0.6173
Δ kurtosis	-	67.676	67.676	67.375	67.527	67.337	67.490	67.833	67.506	67.911	67.910	66.797
out-of sample,weekly												
M. revenues	0.00106	-0.00197	-0.00187	-0.00188	-0.00188	-0.00189	-0.00183	-0.00185	-0.00125	-0.00144	-	-
Variance	0.00124	0.00008	0.00009	0.00009	0.00009	0.00008	0.00009	0.00009	0.00007	0.00007	-	-
Variance red.	-	-93.20%	-93.13%	-93.15%	-93.14%	-93.16%	-92.95%	-93.01%	-94.73%	-94.25%	-	-
VaR	0.06346	0.01889	0.01900	0.01897	0.01898	0.01895	0.01924	0.01917	0.01577	0.01646	-	-
VaR red.	-	-70.24%	-70.06%	-70.11%	-70.09%	-70.13%	-69.68%	-69.80%	-75.15%	-74.07%	-	-
VaR, perc.	0.05360	0.02095	0.01894	0.01908	0.01907	0.01910	0.01908	0.01915	0.02041	0.02150	-	-
VaR, perc., red.	-	-60.91%	-64.67%	-64.40%	-64.42%	-64.37%	-64.40%	-64.28%	-61.93%	-59.88%	-	-
Δ skewness	-	-1.8745	-2.0957	-2.0705	-2.0726	-2.0498	-2.1580	-2.0888	-0.7646	-0.7232	-	-
Δ kurtosis	-	8.041	9.957	9.732	9.751	9.547	10.556	9.877	1.809	1.501	-	-

Table A.30: Soyneams Overview II

Soybeans	Sharpe	Gini 1.5	Gini 2	Gini 5	Gini 10	Gini 20	Gini2 1.5	Gini2 2	Gini2 5	Gini2 10	Gini2 20	GSV 1	GSV 2	GSV 3	GSV 4	GSV 5	VaR
in-sample																	
M. revenues	-	-0.00017	-0.00018	-0.00018	-0.00019	-0.00020	-0.00019	-0.00020	-0.00019	-0.00019	-0.00018	-0.00020	-0.00018	-0.00018	-0.00017	-0.00016	-0.00021
Variance	-	0.00005	0.00005	0.00005	0.00005	0.00005	0.00005	0.00005	0.00005	0.00005	0.00005	0.00005	0.00005	0.00005	0.00005	0.00005	0.00005
Variance red.	-	-87.26%	-87.27%	-87.26%	-87.25%	-87.21%	-87.23%	-87.23%	-87.23%	-87.26%	-87.27%	-87.22%	-87.27%	-87.27%	-87.26%	-87.20%	-87.10%
VaR	-	0.00532	0.00526	0.00517	0.00512	0.00506	0.00508	0.00507	0.00508	0.00513	0.00525	0.00507	0.00521	0.00527	0.00531	0.00562	0.00502
VaR red.	-	-85.27%	-85.43%	-85.68%	-85.83%	-85.99%	-85.93%	-85.95%	-85.93%	-85.79%	-85.45%	-85.98%	-85.56%	-85.41%	-85.29%	-84.43%	-86.10%
VaR, perc.	-	0.00688	0.00690	0.00691	0.00695	0.00692	0.00694	0.00693	0.00694	0.00696	0.00691	0.00693	0.00682	0.00690	0.00687	0.00693	0.00692
VaR, perc., red.	-	-80.84%	-80.77%	-80.75%	-80.63%	-80.73%	-80.68%	-80.69%	-80.68%	-80.62%	-80.76%	-80.71%	-81.00%	-80.78%	-80.87%	-80.71%	-80.73%
Δ skewness	-	-0.5824	-0.5689	-0.5429	-0.5222	-0.4900	-0.5042	-0.5002	-0.5055	-0.5280	-0.5665	-0.4944	-0.5555	-0.5701	-0.5802	-0.6332	-0.4291
Δ kurtosis	-	58.712	58.940	59.257	59.404	59.473	59.465	59.471	59.462	59.371	58.976	59.474	59.123	58.923	58.752	57.349	59.158
out-of sample, daily																	
M. revenues	-	-0.00038	-0.00038	-0.00037	-0.00037	-0.00038	-0.00039	-0.00039	-0.00039	-0.00039	-0.00038	-0.00040	-0.00038	-0.00034	-0.00029	-0.00025	-0.00013
Variance	-	0.00004	0.00004	0.00004	0.00004	0.00004	0.00004	0.00004	0.00004	0.00004	0.00004	0.00004	0.00004	0.00004	0.00004	0.00005	0.00009
Variance red.	-	-83.73%	-83.73%	-83.71%	-83.72%	-83.74%	-83.76%	-83.76%	-83.76%	-83.77%	-83.76%	-83.76%	-83.76%	-83.36%	-81.66%	-78.79%	-58.54%
VaR	-	0.00291	0.00289	0.00287	0.00282	0.00274	0.00270	0.00269	0.00270	0.00274	0.00285	0.00268	0.00281	0.00330	0.00495	0.00716	0.01218
VaR red.	-	-88.25%	-88.33%	-88.41%	-88.63%	-88.96%	-89.12%	-89.14%	-89.09%	-88.93%	-88.50%	-89.19%	-88.65%	-86.69%	-80.04%	-71.09%	-50.84%
VaR, perc.	-	0.00673	0.00673	0.00661	0.00654	0.00644	0.00611	0.00611	0.00600	0.00634	0.00652	0.00611	0.00647	0.00586	0.00705	0.00853	0.01668
VaR, perc., red.	-	-70.45%	-70.46%	-70.98%	-71.28%	-71.74%	-73.19%	-73.17%	-73.64%	-72.15%	-71.35%	-73.16%	-71.58%	-74.25%	-69.06%	-62.54%	-26.74%
Δ skewness	-	-0.6259	-0.6220	-0.6135	-0.6012	-0.5821	-0.5653	-0.5638	-0.5706	-0.5873	-0.6179	-0.5590	-0.6075	-0.6294	-0.6493	-0.6621	0.5796
Δ kurtosis	-	67.022	67.129	67.194	67.485	67.918	68.033	68.049	68.026	67.903	67.403	68.087	67.586	64.146	52.779	39.513	11.445
out-of sample, constant																	
M. revenues	-	-0.00038	-0.00039	-0.00039	-0.00040	-0.00040	-0.00040	-0.00040	-0.00040	-0.00040	-0.00039	-0.00040	-0.00039	-0.00039	-0.00038	-0.00037	-0.00041
Variance	-	0.00004	0.00004	0.00004	0.00004	0.00004	0.00004	0.00004	0.00004	0.00004	0.00004	0.00004	0.00004	0.00004	0.00004	0.00004	0.00004
Variance red.	-	-83.71%	-83.73%	-83.74%	-83.74%	-83.73%	-83.74%	-83.74%	-83.74%	-83.74%	-83.73%	-83.73%	-83.74%	-83.73%	-83.71%	-83.61%	-83.66%
VaR	-	0.00288	0.00284	0.00277	0.00273	0.00268	0.00270	0.00270	0.00270	0.00274	0.00283	0.00269	0.00280	0.00284	0.00288	0.00311	0.00264
VaR red.	-	-88.36%	-88.53%	-88.81%	-88.98%	-89.17%	-89.10%	-89.12%	-89.09%	-88.94%	-88.56%	-89.15%	-88.68%	-88.52%	-88.39%	-87.47%	-89.33%
VaR, perc.	-	0.00621	0.00607	0.00609	0.00622	0.00641	0.00633	0.00636	0.00633	0.00619	0.00605	0.00639	0.00601	0.00608	0.00619	0.00676	0.00617
VaR, perc., red.	-	-72.72%	-73.35%	-73.25%	-72.68%	-71.84%	-72.19%	-72.09%	-72.22%	-72.83%	-73.46%	-71.94%	-73.62%	-73.29%	-72.82%	-70.32%	-72.90%
Δ skewness	-	0.3783	-0.6093	-0.6003	-0.5828	-0.5688	-0.5468	-0.5566	-0.5538	-0.5574	-0.5727	-0.5987	-0.5498	-0.5913	-0.6011	-0.6079	-0.6427
Δ kurtosis	-	6.813	67.045	67.280	67.620	67.797	67.926	67.889	67.903	67.885	67.755	67.317	67.918	67.473	67.262	67.086	65.704
out-of sample,weekly																	
M. revenues	-	-0.00188	-0.00188	-0.00187	-0.00188	-0.00189	-0.00197	-0.00197	-0.00196	-0.00193	-0.00189	-0.00199	-0.00190	-0.00174	-0.00150	-0.00126	-0.00081
Variance	-	0.00009	0.00009	0.00009	0.00009	0.00008	0.00008	0.00008	0.00008	0.00008	0.00008	0.00008	0.00008	0.00009	0.00012	0.00016	0.00024
Variance red.	-	-93.14%	-93.13%	-93.11%	-93.14%	-93.19%	-93.24%	-93.24%	-93.23%	-93.23%	-93.22%	-93.24%	-93.23%	-92.82%	-90.70%	-87.21%	-80.68%
VaR	-	0.01899	0.01900	0.01902	0.01898	0.01890	0.01882	0.01882	0.01883	0.01885	0.01888	0.01881	0.01885	0.01930	0.02160	0.02505	0.02452
VaR red.	-	-70.07%	-70.07%	-70.03%	-70.10%	-70.22%	-70.33%	-70.34%	-70.32%	-70.29%	-70.25%	-70.37%	-70.30%	-69.58%	-65.96%	-60.53%	-61.36%
VaR, perc.	-	0.01924	0.01910	0.01904	0.01878	0.01858	0.02106	0.02107	0.02082	0.02043	0.01913	0.02108	0.01909	0.01676	0.01839	0.01783	0.02503
VaR, perc., red.	-	-64.11%	-64.37%	-64.49%	-64.97%	-65.34%	-60.71%	-60.69%	-61.17%	-61.88%	-64.32%	-60.68%	-64.39%	-68.73%	-65.70%	-66.74%	-53.31%
Δ skewness	-	-2.0365	-2.0581	-2.1091	-2.1134	-2.1127	-1.8693	-1.8667	-1.8995	-1.9502	-2.0054	-1.8559	-2.0287	-2.3606	-2.8725	-2.9070	0.6879
Δ kurtosis	-	9.412	9.611	10.091	10.160	10.236	8.052	8.037	8.294	8.680	9.116	7.998	9.410	12.847	18.623	19.969	1.565

Table A.31: Wheat Overview I

Wheat	No	Naive	OLS,si	OLS,sp	ECM,si	ECM,sp	GARCH,si	GARCH,sp	bGARCH,si	bGARCH,sp	bGARCH,si,a	bGARCH,sp,a
in-sample												
M. revenues	0.00046	0.00065	0.00068	0.00068	0.00068	0.00068	0.00069	-	0.00098	0.00098	0.00068	-
Variance	0.00127	0.00039	0.00038	0.00038	0.00038	0.00038	0.00038	-	0.00039	0.00039	0.00038	-
Variance red.	-	-68.86%	-70.21%	-70.21%	-70.21%	-70.21%	-70.11%	-	-69.47%	-69.50%	-70.17%	-
VaR	0.05915	0.02084	0.01865	0.01864	0.01864	0.01864	0.01862	-	0.01647	0.01660	0.01879	-
VaR red.	-	-64.77%	-68.47%	-68.48%	-68.49%	-68.49%	-68.52%	-	-72.16%	-71.93%	-68.24%	-
VaR, perc.	0.05807	0.02417	0.02451	0.02450	0.02448	0.02448	0.02361	-	0.02319	0.02294	0.02417	-
VaR, perc., red.	-	-58.38%	-57.79%	-57.81%	-57.85%	-57.84%	-59.34%	-	-60.06%	-60.50%	-58.37%	-
Δ skewness	-	0.2972	0.3986	0.3994	0.4002	0.4000	0.4193	-	0.6289	0.6123	0.3843	-
Δ kurtosis	-	26.293	29.289	29.292	29.294	29.293	29.149	-	32.033	31.914	29.163	-
out-of sample, daily												
M. revenues	-0.00027	0.00048	0.00054	0.00055	0.00054	0.00055	0.00055	-	0.00047	-0.00027	-	-
Variance	0.00056	0.00022	0.00024	0.00024	0.00024	0.00024	0.00024	-	0.00023	0.00056	-	-
Variance red.	-	-60.01%	-56.93%	-56.90%	-56.87%	-56.97%	-55.91%	-	-58.95%	0.00%	-	-
VaR	0.03608	0.01313	0.01483	0.01485	0.01487	0.01479	0.01535	-	0.01495	0.03608	-	-
VaR red.	-	-63.62%	-58.89%	-58.85%	-58.80%	-59.01%	-57.46%	-	-58.58%	0.00%	-	-
VaR, perc.	0.03643	0.01377	0.01401	0.01402	0.01401	0.01401	0.01426	-	0.01410	0.03643	-	-
VaR, perc., red.	-	-62.22%	-61.54%	-61.52%	-61.54%	-61.53%	-60.86%	-	-61.29%	0.00%	-	-
Δ skewness	-	-0.3913	-0.3422	-0.3413	-0.3413	-0.3408	-0.3186	-	-0.4269	0.0000	-	-
Δ kurtosis	-	37.654	33.110	33.068	33.024	33.202	31.705	-	32.712	0.000	-	-
out-of sample, constant												
M. revenues	-0.00027	0.00048	0.00060	0.00060	0.00060	0.00060	0.00063	-	0.00044	0.00044	0.00058	-
Variance	0.00056	0.00022	0.00025	0.00025	0.00025	0.00025	0.00026	-	0.00022	0.00022	0.00024	-
Variance red.	-	-60.01%	-55.61%	-55.55%	-55.49%	-55.51%	-53.74%	-	-60.57%	-60.53%	-56.61%	-
VaR	0.03608	0.01313	0.01577	0.01581	0.01584	0.01583	0.01683	-	0.01283	0.01285	0.01519	-
VaR red.	-	-63.62%	-56.30%	-56.20%	-56.10%	-56.13%	-53.37%	-	-64.45%	-64.39%	-57.91%	-
VaR, perc.	0.03643	0.01377	0.01488	0.01484	0.01480	0.01482	0.01522	-	0.01405	0.01404	0.01443	-
VaR, perc., red.	-	-62.22%	-59.17%	-59.27%	-59.36%	-59.33%	-58.22%	-	-61.43%	-61.46%	-60.41%	-
Δ skewness	-	-0.3913	-0.3913	-0.3494	-0.3488	-0.3482	-0.3483	-	-0.3307	-0.3922	-0.3924	-
Δ kurtosis	-	37.654	37.654	30.961	30.873	30.786	30.813	-	28.456	38.359	38.316	-
out-of sample,weekly												
M. revenues	-0.00027	0.00048	0.00054	0.00055	0.00054	0.00055	0.00055	-	0.00051	-	-	-
Variance	0.00056	0.00022	0.00024	0.00024	0.00024	0.00024	0.00024	-	0.00023	-	-	-
Variance red.		-60.01%	-56.98%	-56.95%	-56.92%	-57.02%	-55.98%	-	-58.26%	-	-	-
VaR	0.03608	0.01313	0.01482	0.01484	0.01486	0.01478	0.01533	-	0.01425	-	-	-
VaR red.		-63.62%	-58.92%	-58.88%	-58.83%	-59.04%	-57.51%	-	-60.50%	-	-	-
VaR, perc.	0.03643	0.01377	0.01401	0.01402	0.01401	0.01401	0.01425	-	0.01317	-	-	-
VaR, perc., red.		-62.22%	-61.55%	-61.52%	-61.54%	-61.54%	-60.90%	-	-63.84%	-	-	-
Δ skewness		-0.3913	-0.3438	-0.3433	-0.3431	-0.3427	-0.3173	-	-0.7361	-	-	-
Δ kurtosis		37.654	33.139	33.098	33.054	33.234	31.704	-	39.401	-	-	-

Table A.32: Wheat Overview II

Wheat	Sharpe	Gini 1.5	Gini 2	Gini 5	Gini 10	Gini 20	Gini2 1.5	Gini2 2	Gini2 5	Gini2 10	Gini2 20	GSV 1	GSV 2	GSV 3	GSV 4	GSV 5	VaR
in-sample																	
M. revenues	0.00071	0.00068	0.00068	0.00069	0.00069	0.00069	0.00068	0.00068	0.00068	0.00069	0.00069	0.00068	0.00069	0.00070	0.00071	0.00073	0.00069
Variance	0.00039	0.00038	0.00038	0.00038	0.00038	0.00038	0.00038	0.00038	0.00038	0.00038	0.00038	0.00038	0.00038	0.00038	0.00039	0.00042	0.00038
Variance red.	-69.37%	-70.20%	-70.21%	-70.19%	-70.16%	-70.08%	-70.19%	-70.19%	-70.21%	-70.20%	-70.12%	-70.17%	-70.19%	-69.96%	-69.07%	-67.22%	-70.17%
VaR	0.01924	0.01869	0.01865	0.01860	0.01860	0.01863	0.01874	0.01873	0.01866	0.01861	0.01861	0.01878	0.01860	0.01871	0.01953	0.02137	0.01860
VaR red.	-67.47%	-68.40%	-68.47%	-68.54%	-68.55%	-68.50%	-68.32%	-68.34%	-68.45%	-68.53%	-68.53%	-68.25%	-68.55%	-68.36%	-66.98%	-63.87%	-68.56%
VaR, perc.	0.02385	0.02432	0.02451	0.02372	0.02357	0.02344	0.02412	0.02417	0.02445	0.02401	0.02360	0.02410	0.02355	0.02310	0.02400	0.02503	0.02357
VaR, perc., red.	-58.92%	-58.12%	-57.80%	-59.16%	-59.40%	-59.64%	-58.47%	-58.38%	-57.89%	-58.65%	-59.35%	-58.49%	-59.44%	-60.22%	-58.66%	-56.90%	-59.41%
Δ skewness	0.4473	0.3930	0.3985	0.4073	0.4128	0.4218	0.3885	0.3896	0.3969	0.4051	0.4180	0.3850	0.4088	0.4294	0.4520	0.4619	0.4120
Δ kurtosis	27.749	29.257	29.289	29.285	29.244	29.098	29.216	29.227	29.282	29.293	29.172	29.173	29.277	28.874	27.185	23.976	29.253
out-of sample, daily																	
M. revenues	0.00095	0.00054	0.00055	0.00055	0.00055	0.00055	0.00054	0.00054	0.00054	0.00055	0.00055	0.00054	0.00055	0.00056	0.00055	0.00057	0.00054
Variance	0.00045	0.00024	0.00024	0.00024	0.00024	0.00024	0.00024	0.00024	0.00024	0.00024	0.00025	0.00024	0.00025	0.00025	0.00026	0.00027	0.00024
Variance red.	-18.12%	-57.16%	-56.88%	-56.51%	-56.34%	-55.91%	-57.54%	-57.44%	-56.80%	-56.08%	-55.20%	-57.44%	-55.67%	-54.43%	-53.09%	-51.09%	-55.97%
VaR	0.03091	0.01473	0.01489	0.01510	0.01519	0.01544	0.01451	0.01457	0.01493	0.01533	0.01579	0.01458	0.01556	0.01610	0.01640	0.01694	0.01542
VaR red.	-14.35%	-59.18%	-58.73%	-58.16%	-57.89%	-57.20%	-59.77%	-59.63%	-58.64%	-57.51%	-56.24%	-59.60%	-56.87%	-55.39%	-54.55%	-53.04%	-57.27%
VaR, perc.	0.02809	0.01402	0.01402	0.01404	0.01405	0.01450	0.01366	0.01375	0.01401	0.01433	0.01477	0.01339	0.01455	0.01525	0.01652	0.01817	0.01450
VaR, perc., red.	-22.89%	-61.52%	-61.53%	-61.46%	-61.44%	-60.20%	-62.52%	-62.25%	-61.55%	-60.68%	-59.47%	-63.26%	-60.06%	-58.13%	-54.65%	-50.11%	-60.21%
Δ skewness	-0.2621	-0.3460	-0.3433	-0.3391	-0.3366	-0.3308	-0.3557	-0.3545	-0.3450	-0.3336	-0.3145	-0.3561	-0.3256	-0.2713	-0.1585	-0.0487	-0.3445
Δ kurtosis	7.693	33.368	32.965	32.447	32.208	31.573	33.981	33.850	32.921	31.869	30.653	33.831	31.260	29.537	27.781	25.660	31.807
out-of sample, constant																	
M. revenues	0.00069	0.00059	0.00059	0.00061	0.00062	0.00063	0.00058	0.00058	0.00059	0.00060	0.00063	0.00058	0.00061	0.00065	0.00071	0.00077	0.00062
Variance	0.00028	0.00024	0.00025	0.00025	0.00025	0.00026	0.00024	0.00024	0.00025	0.00025	0.00026	0.00024	0.00025	0.00026	0.00029	0.00032	0.00025
Variance red.	-49.40%	-56.03%	-55.62%	-54.91%	-54.40%	-53.47%	-56.33%	-56.26%	-55.74%	-55.09%	-53.88%	-56.56%	-54.77%	-52.53%	-48.14%	-41.82%	-54.48%
VaR	0.01908	0.01553	0.01576	0.01617	0.01646	0.01697	0.01535	0.01539	0.01570	0.01607	0.01675	0.01521	0.01625	0.01748	0.01969	0.02248	0.01641
VaR red.	-47.12%	-56.97%	-56.31%	-55.18%	-54.38%	-52.96%	-57.47%	-57.35%	-56.50%	-55.47%	-53.58%	-57.84%	-54.96%	-51.56%	-45.43%	-37.71%	-54.51%
VaR, perc.	0.01768	0.01488	0.01488	0.01522	0.01522	0.01522	0.01470	0.01475	0.01495	0.01514	0.01522	0.01449	0.01522	0.01556	0.01809	0.02023	0.01522
VaR, perc., red.	-51.47%	-59.15%	-59.15%	-58.23%	-58.22%	-58.22%	-59.65%	-59.53%	-58.97%	-58.44%	-58.22%	-60.24%	-58.22%	-57.29%	-50.34%	-44.47%	-58.22%
Δ skewness	-0.3605	-0.2911	-0.3537	-0.3495	-0.3423	-0.3372	-0.3280	-0.3568	-0.3561	-0.3507	-0.3442	-0.3320	-0.3592	-0.3408	-0.3190	-0.2807	-0.2355
Δ kurtosis	32.514	23.524	31.552	30.973	29.986	29.309	28.114	31.992	31.885	31.139	30.243	28.632	32.326	29.798	26.964	22.293	17.204
out-of sample,weekly																	
M. revenues	0.00085	0.00054	0.00055	0.00055	0.00055	0.00055	0.00054	0.00054	0.00054	0.00055	0.00055	0.00054	0.00055	0.00056	0.00054	0.00055	0.00054
Variance	0.00046	0.00024	0.00024	0.00024	0.00024	0.00024	0.00024	0.00024	0.00024	0.00024	0.00025	0.00024	0.00025	0.00025	0.00026	0.00027	0.00024
Variance red.	-17.70%	-57.14%	-56.87%	-56.50%	-56.33%	-55.89%	-57.53%	-57.43%	-56.80%	-56.07%	-55.18%	-57.42%	-55.65%	-54.38%	-52.97%	-51.01%	-55.93%
VaR	0.03098	0.01473	0.01490	0.01511	0.01520	0.01545	0.01452	0.01457	0.01493	0.01534	0.01580	0.01459	0.01557	0.01612	0.01645	0.01706	0.01542
VaR red.	-14.15%	-59.17%	-58.72%	-58.13%	-57.87%	-57.18%	-59.76%	-59.62%	-58.62%	-57.48%	-56.21%	-59.56%	-56.84%	-55.33%	-54.41%	-52.74%	-57.28%
VaR, perc.	0.02896	0.01402	0.01402	0.01404	0.01405	0.01451	0.01364	0.01374	0.01402	0.01438	0.01477	0.01339	0.01456	0.01525	0.01654	0.01817	0.01454
VaR, perc., red.	-20.52%	-61.52%	-61.53%	-61.46%	-61.44%	-60.17%	-62.56%	-62.28%	-61.51%	-60.52%	-59.45%	-63.26%	-60.03%	-58.13%	-54.61%	-50.13%	-60.10%
Δ skewness	-0.2476	-0.3470	-0.3445	-0.3409	-0.3378	-0.3307	-0.3559	-0.3547	-0.3458	-0.3346	-0.3162	-0.3575	-0.3280	-0.2789	-0.1792	-0.0814	-0.3338
Δ kurtosis	7.504	33.373	32.973	32.450	32.201	31.559	33.975	33.844	32.917	31.862	30.646	33.824	31.266	29.593	27.973	25.822	31.688

Appendix B

Figures

Figure B.1: Spot and futures prices

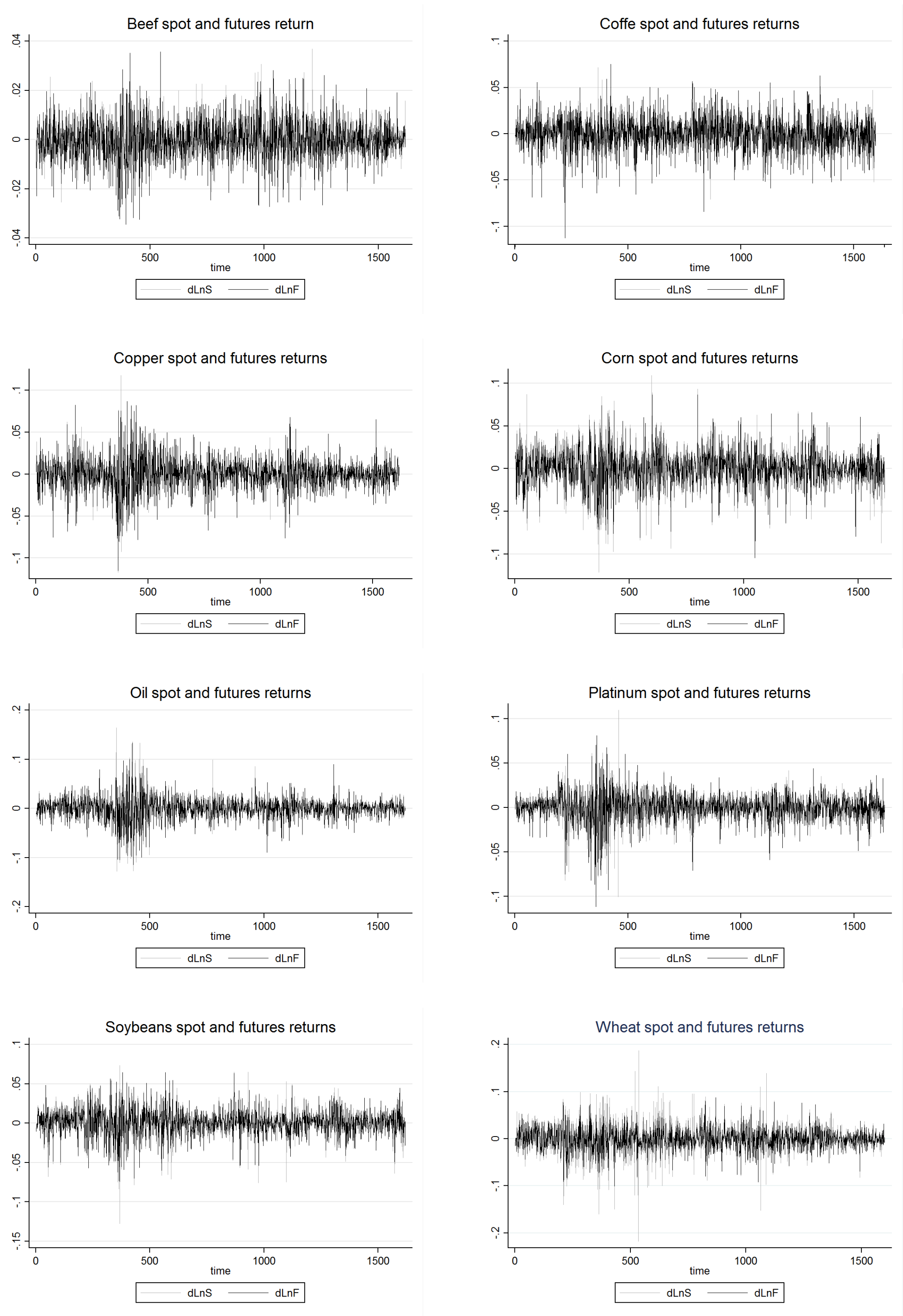
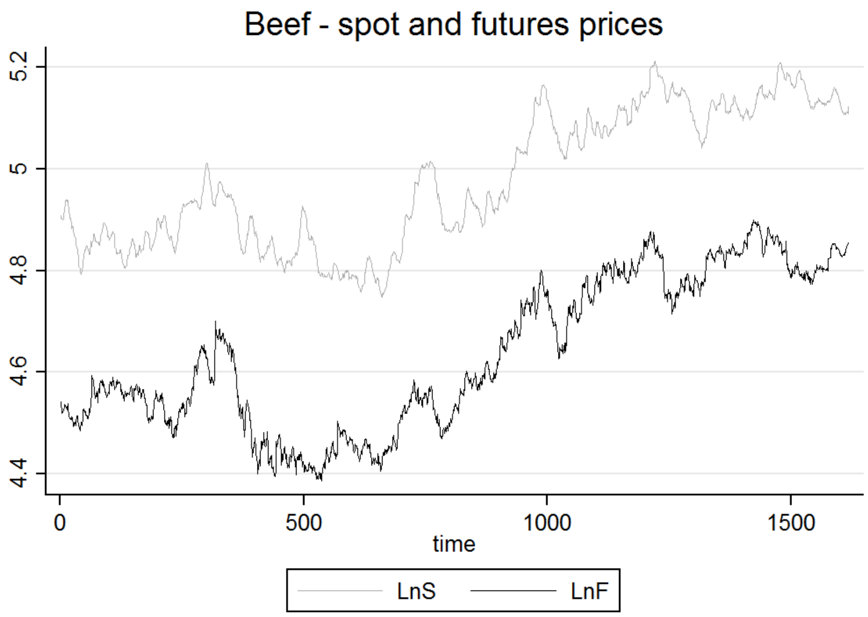


Figure B.2: Spot and futures prices



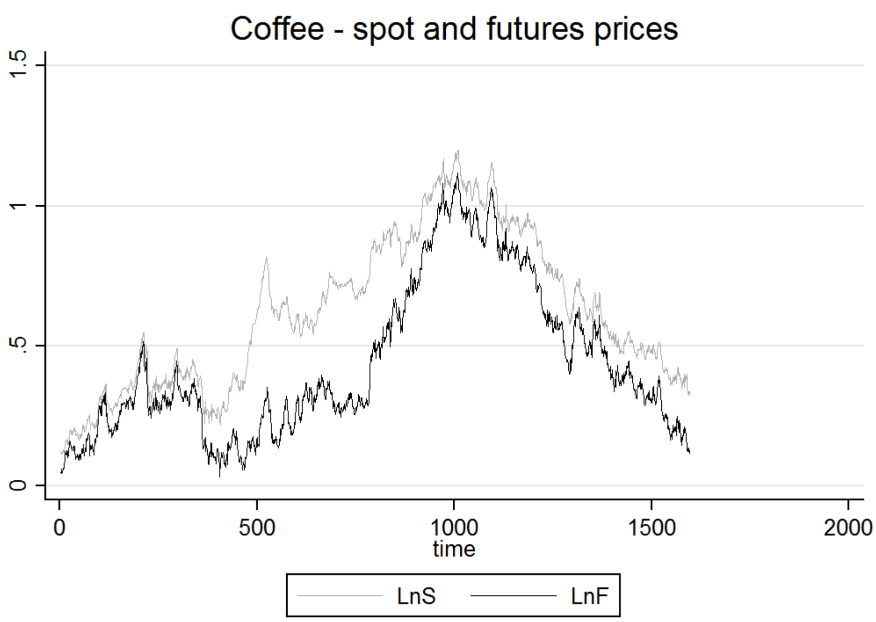


Figure B.3: Beef - overview of in-sample bivariate GARCH HR

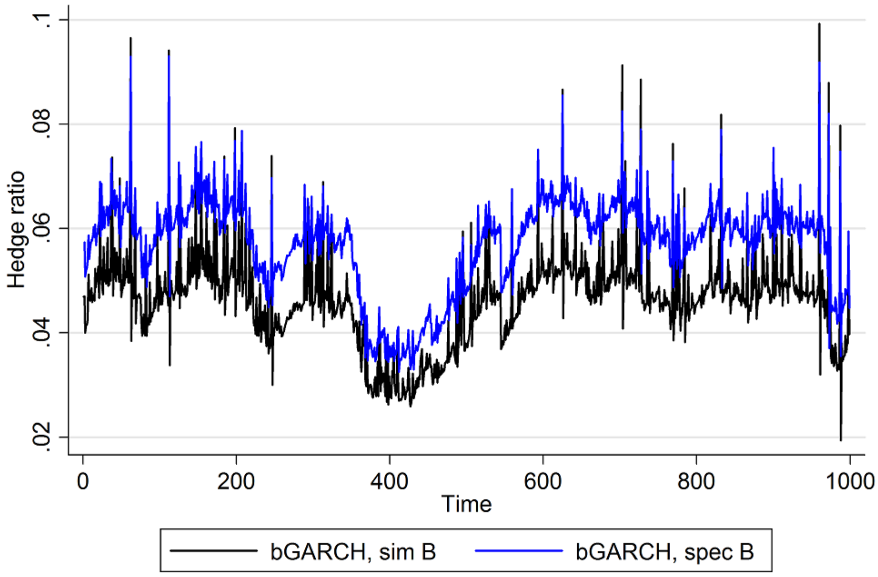


Figure B.4: Beef - correlation between spot and futures returns, out-of-sample

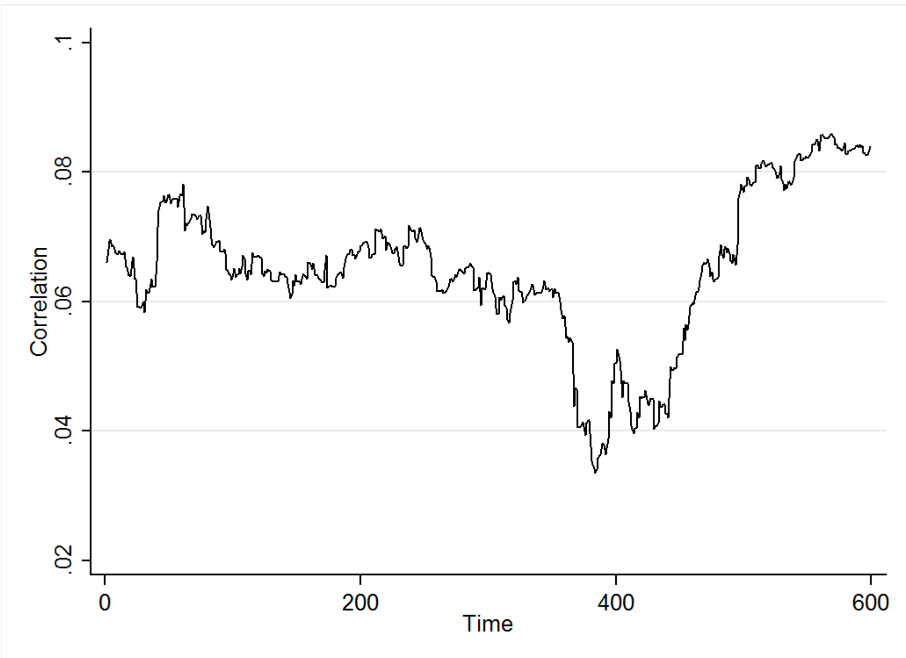


Figure B.5: Beef - overview of in-sample constant HR

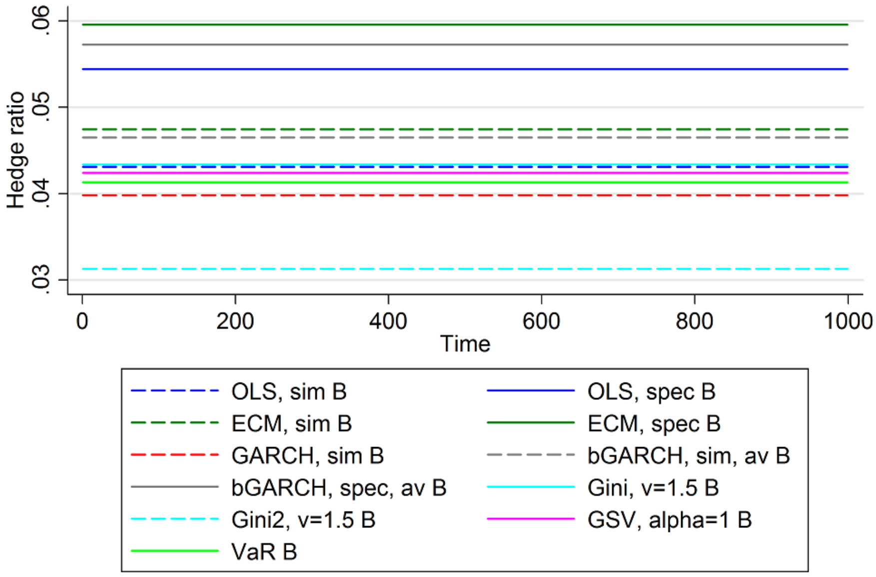


Figure B.6: Beef - overview of average out-of-sample HR

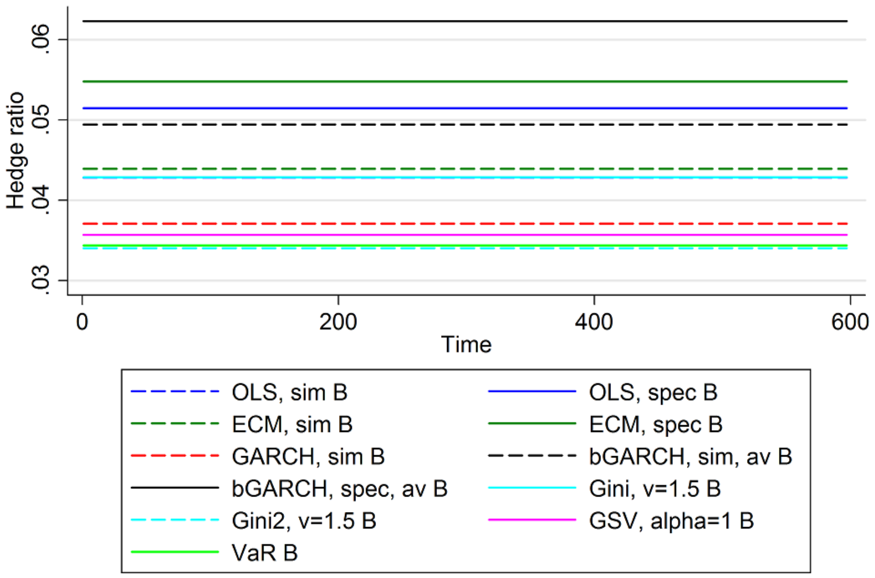


Figure B.7: Coffee - overview of in-sample constant HR

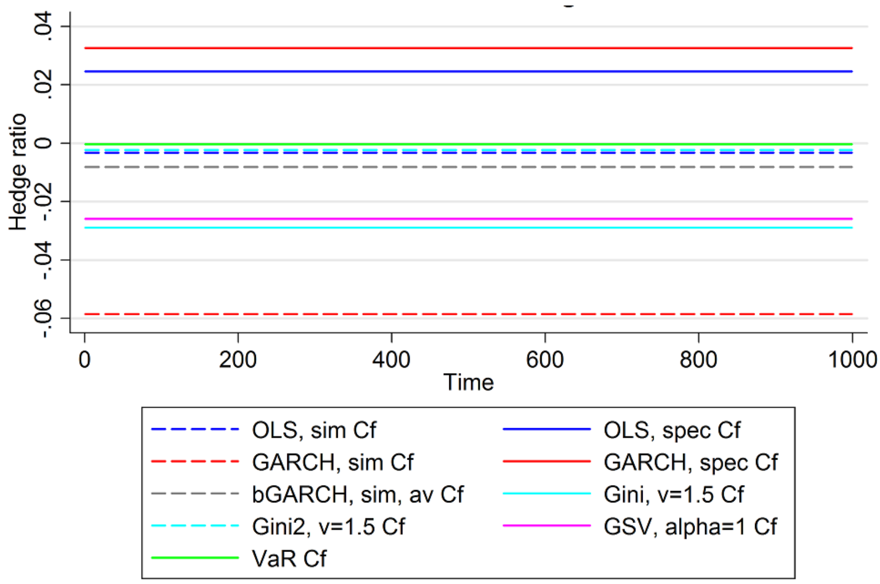


Figure B.8: Coffee - overview of average out-of-sample HR

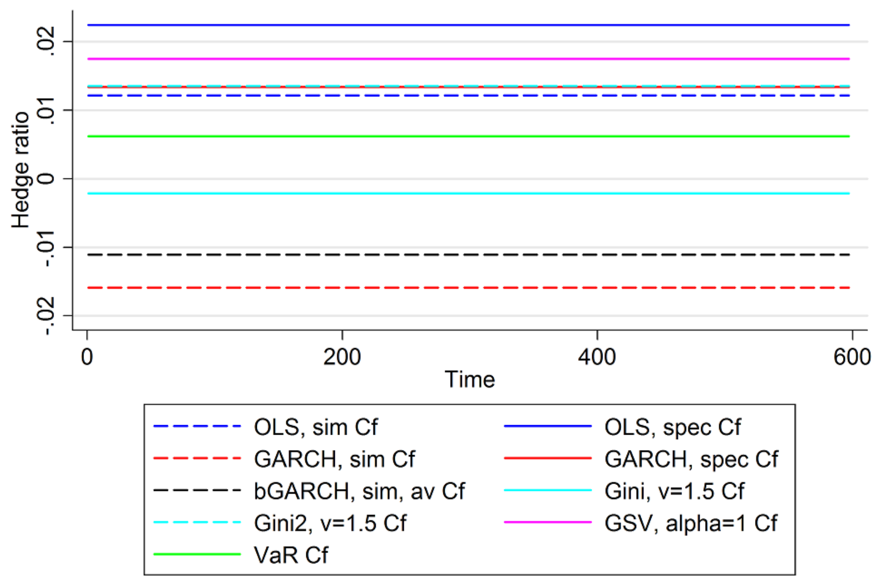


Figure B.9: Copper - overview of in-sample constant HR

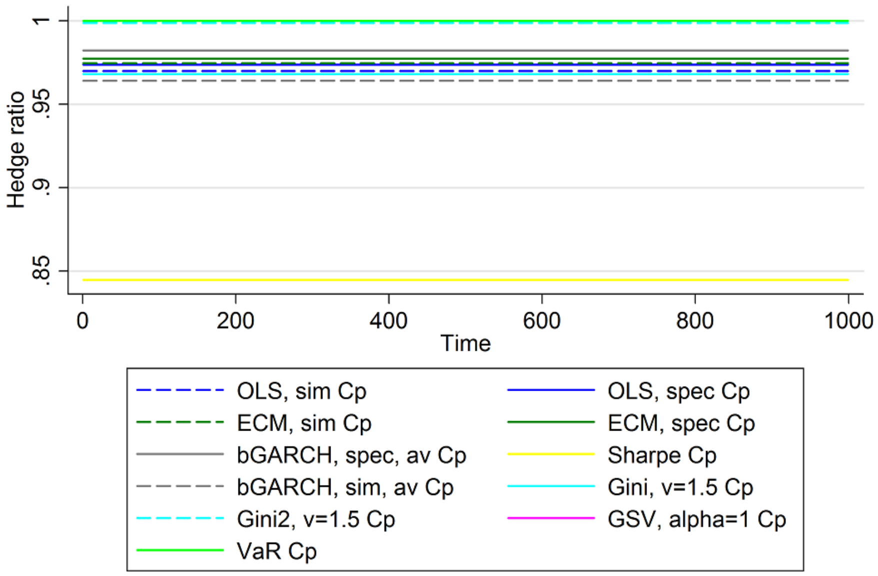


Figure B.10: Copper - overview of average out-of-sample HR

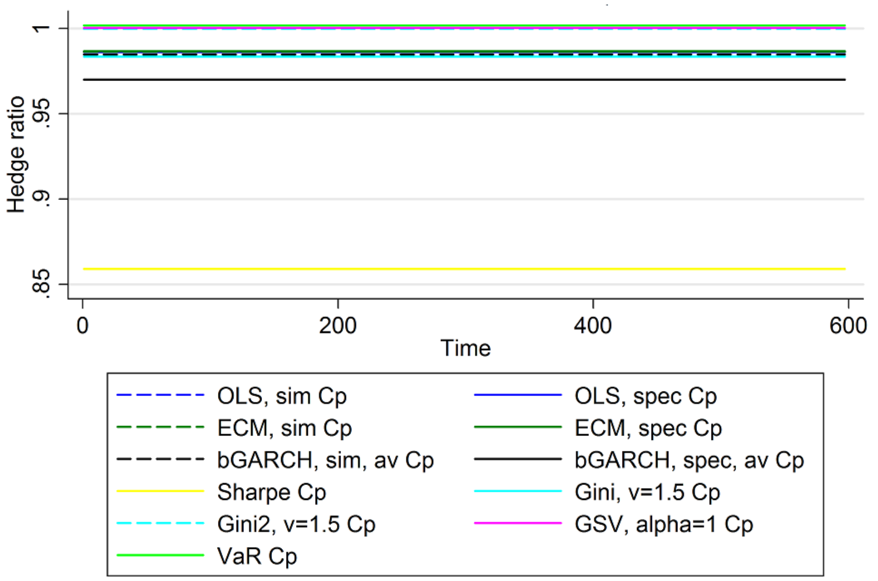


Figure B.11: Copper - overview of in-sample bivariate GARCH HR

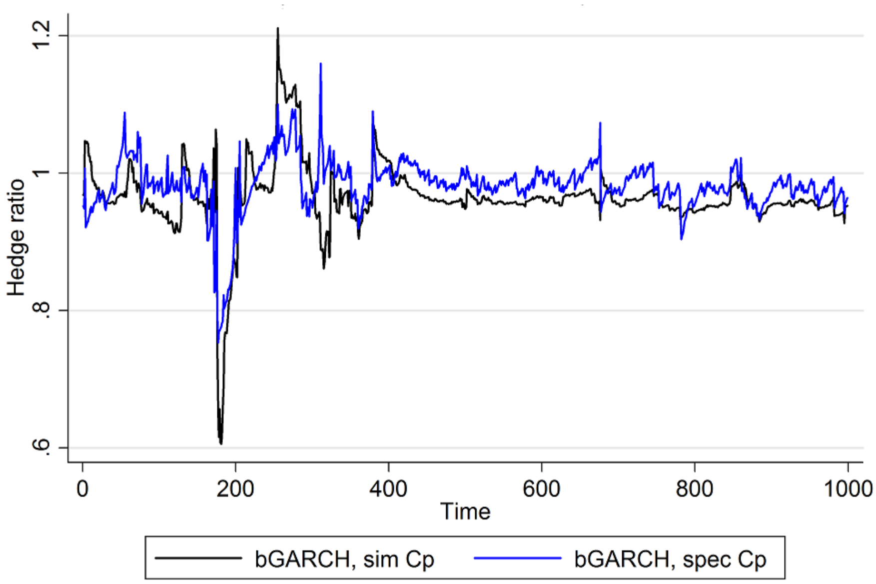


Figure B.12: Corn - overview of in-sample bivariate GARCH HR

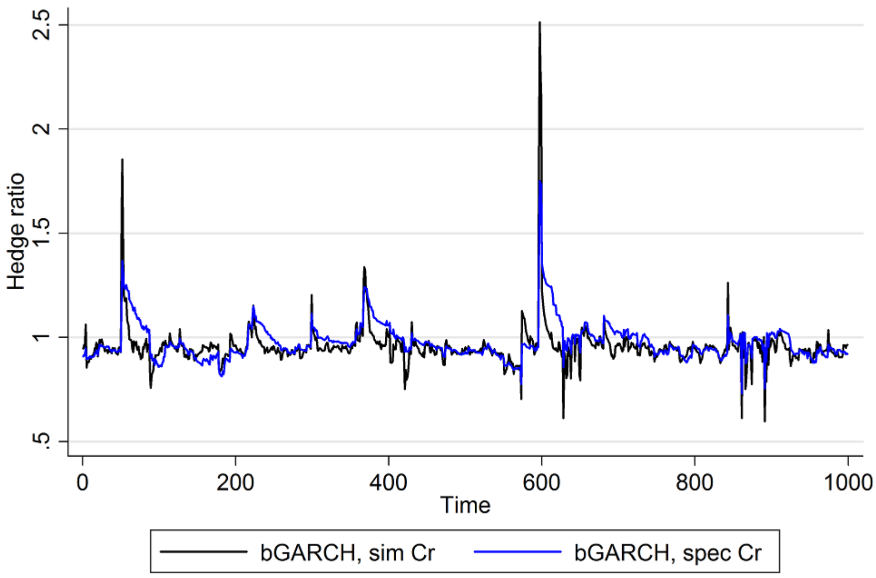


Figure B.13: Corn - overview of in-sample constant HR

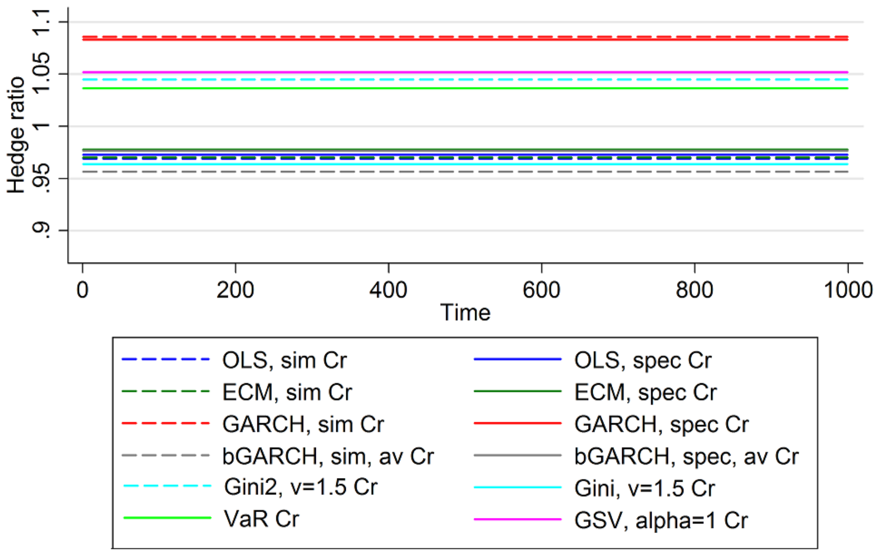


Figure B.14: Corn - overview of average out-of-sample HR

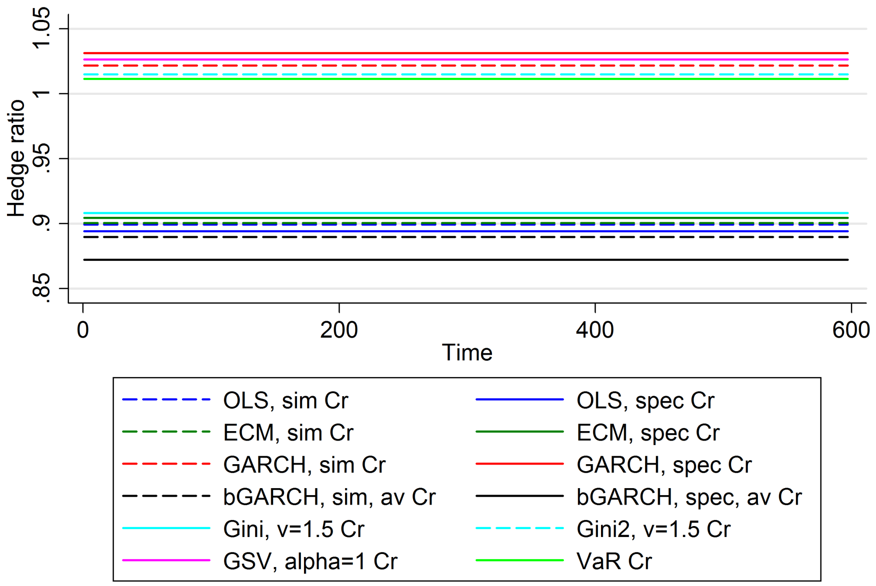


Figure B.15: Oil - overview of in-sample constant HR

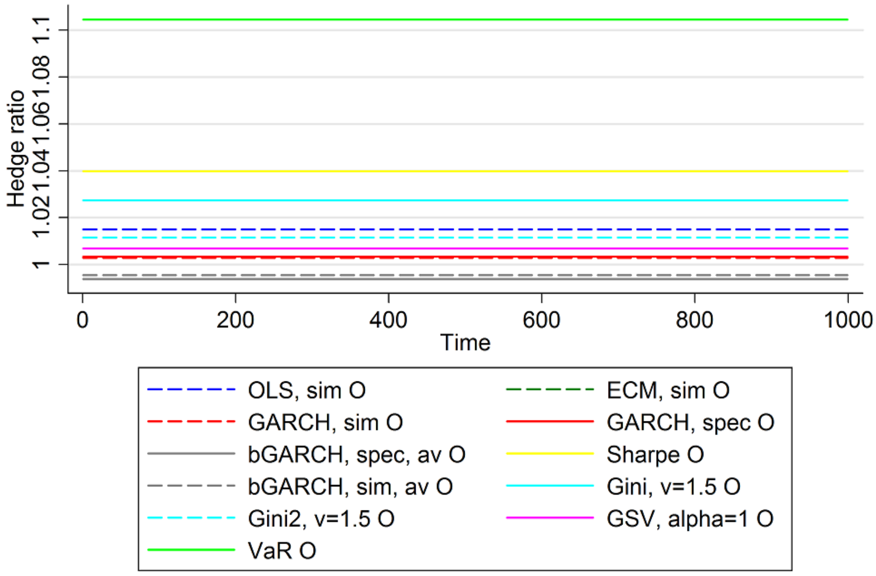


Figure B.16: Oil - overview of average out-of-sample HR

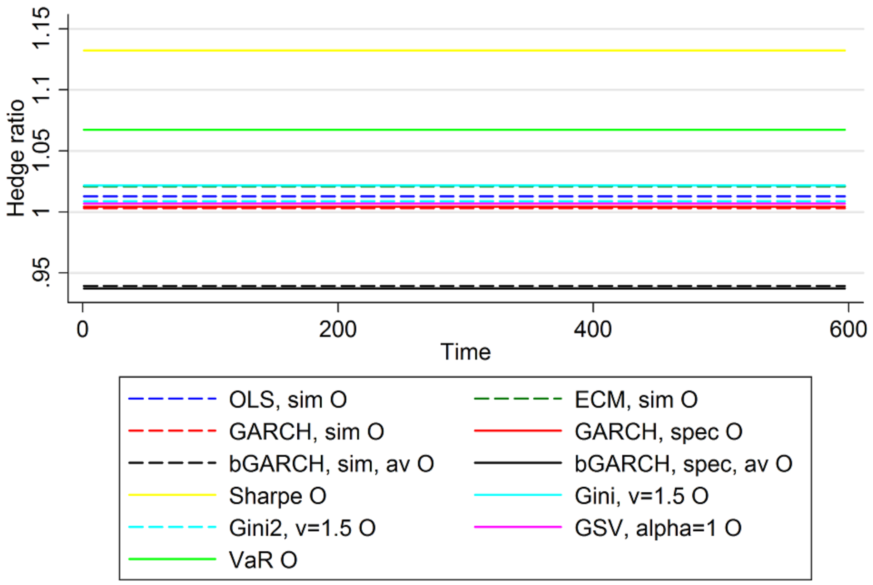


Figure B.17: Oil - overview of in-sample bivariate GARCH HR

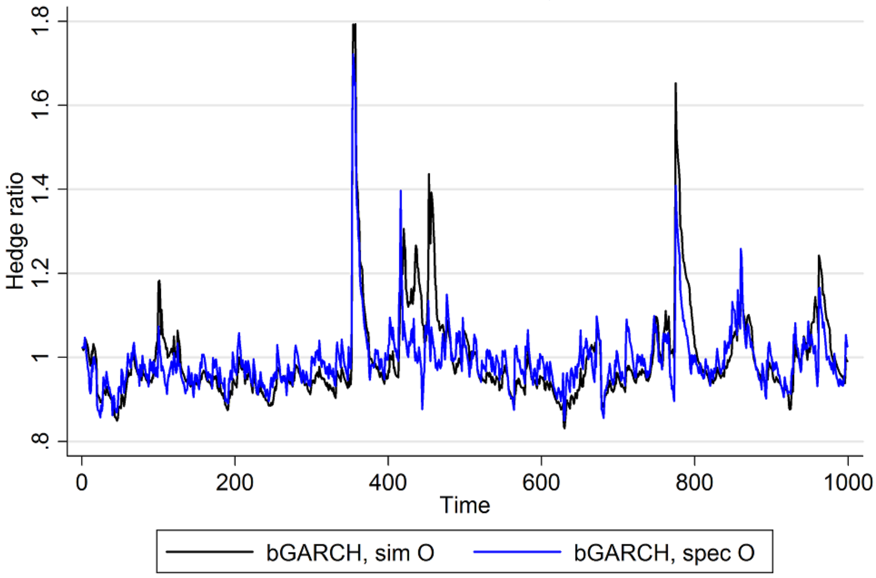


Figure B.18: Platinum - overview of in-sample bivariate GARCH HR

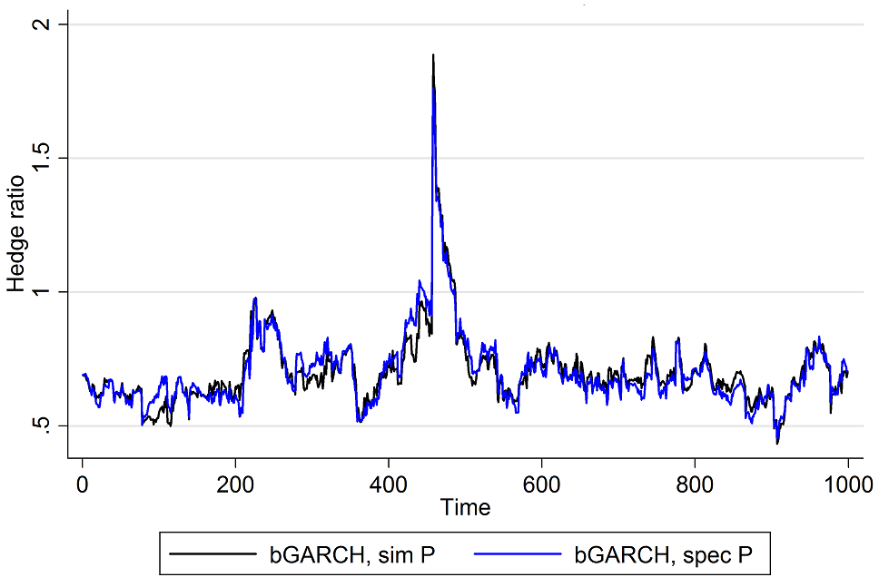


Figure B.19: Platinum - overview of in-sample constant HR

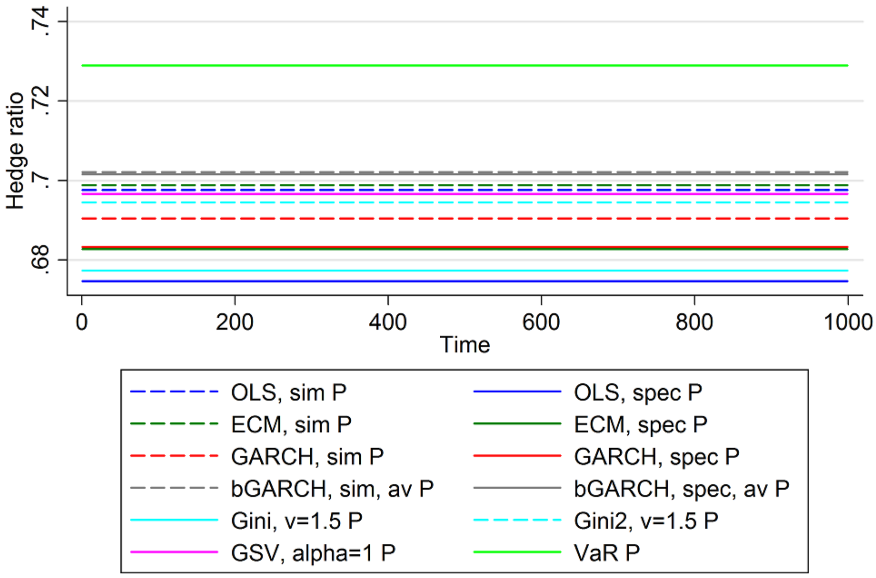


Figure B.20: Platinum - overview of average out-of-sample HR

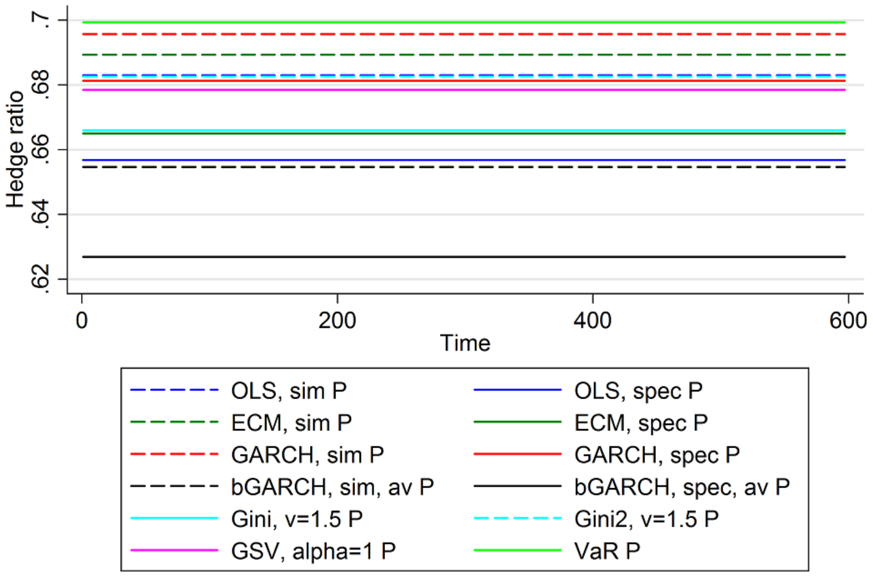


Figure B.21: Soybeans - overview of in-sample constant HR

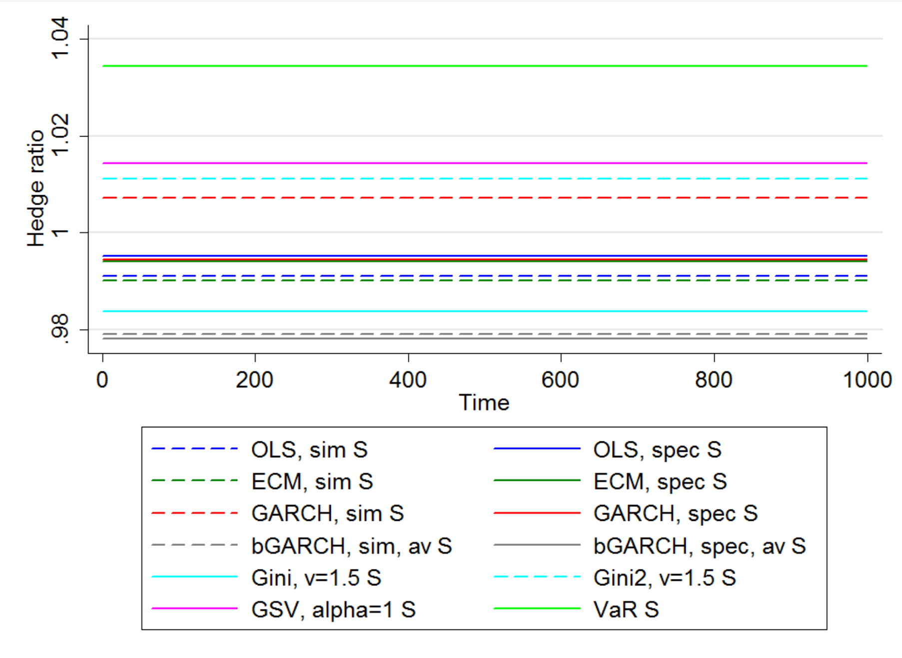


Figure B.22: Soybeans - overview of average out-of-sample HR

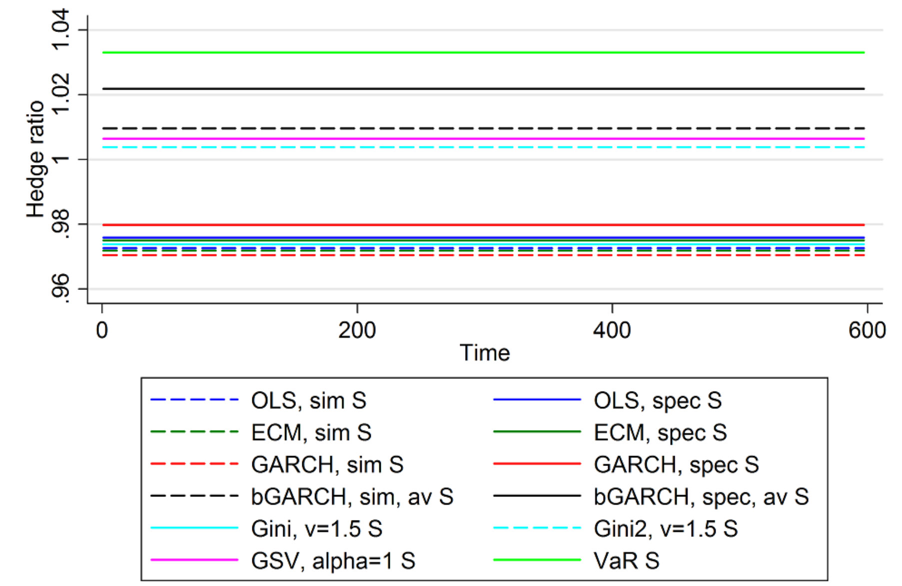


Figure B.23: Soybeans - overview of in-sample bivariate GARCH HR

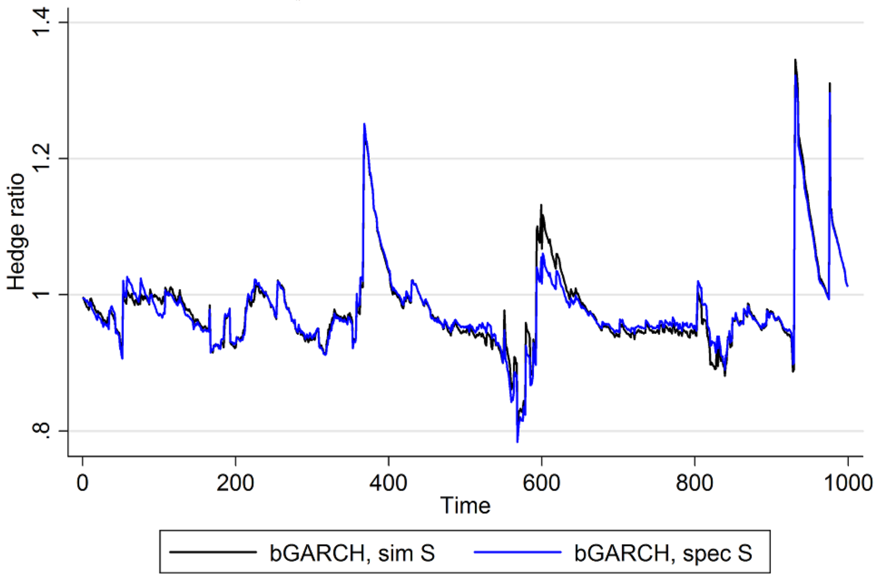


Figure B.24: Wheat - overview of in-sample constant HR

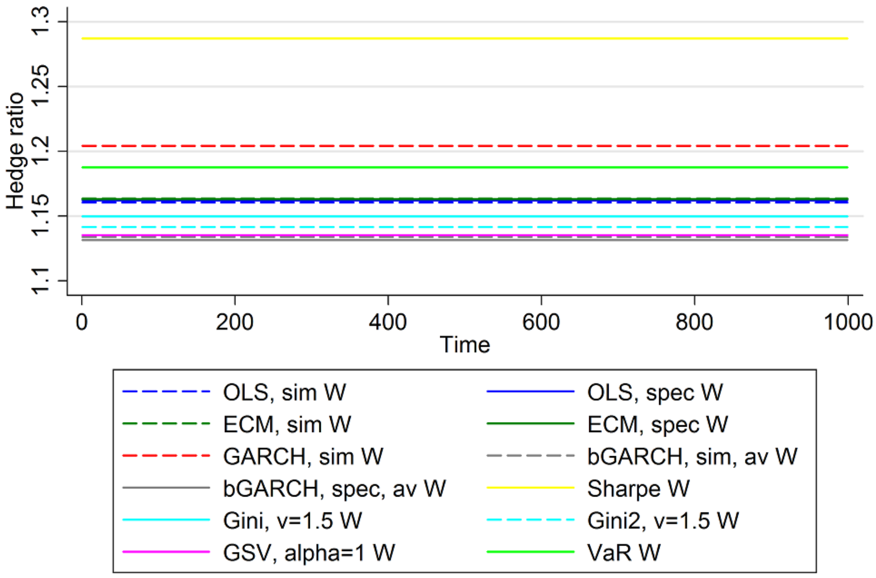
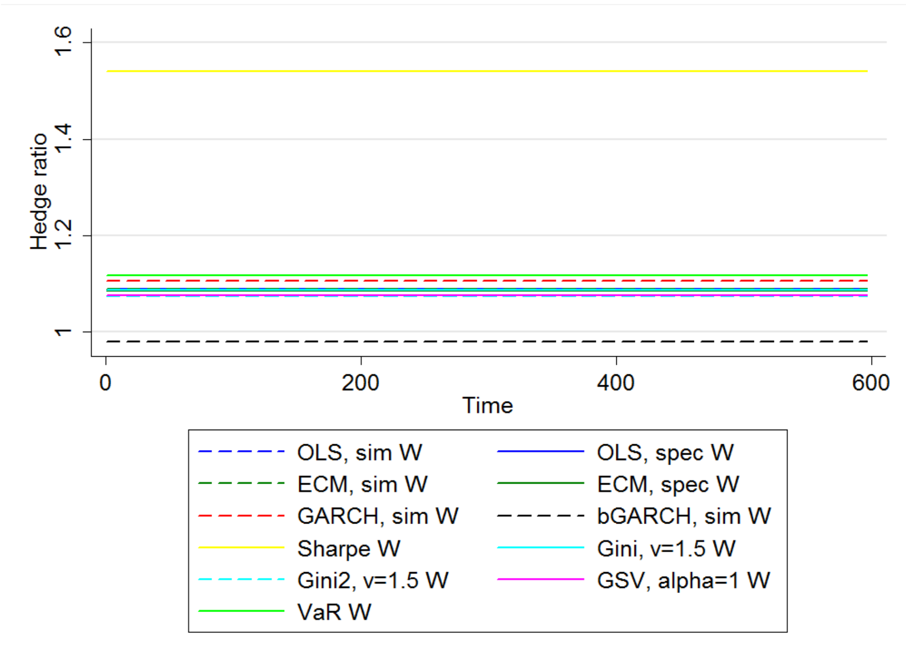


Figure B.25: Wheat - overview of average out-of-sample HR



Appendix C

STATA and Matlab codes

C.1 STATA

Error correction model

```
program ECM
forvalue i=1/600{
generate m=‘i’
generate j=999+‘i’
regress LnS LnF in ‘=m’/‘=j’, noconstant
generate a=_b[LnF]
generate z=LnS-a*LnF
regress dLnS dLnF l.dLnS l.dLnF l.z in ‘=m’/‘=j’
generate HRecm‘i’=_b[dLnF]
drop m
drop j
drop a
drop z
}
end ECM
```

GARCH

```
program GARCH
forvalue i=1/600{
generate m=‘i’
generate j=999+‘i’
regress LnS LnF in ‘=m’/‘=j’, noconstant
```

```
generate a=_b[LnF]
generate z=LnS-a*LnF
arch dLnS dLnF l.dLnS l.dLnF l.z in ‘=m’/‘=j’, arch(1/1) garch(1/1)
generate HRgarchecm‘i’=_b[dLnF]
drop m
drop j
drop a
drop z
}
end
GARCH
```

bivariate GARCH

```
program cccGARCH
forvalue i=1/600{
generate m=‘i’
generate j=999+‘i’
regress LnS LnF in ‘=m’/‘=j’, noconstant
generate a=_b[LnF]
generate z=LnS-a*LnF
mgarch ccc (dLnS=l.z) (dLnF=l.z) in ‘=m’/‘=j’, arch(1/1) garch(1/1)
predict H*, variance
generate HRstandccc‘i’=H_dLnF_dLnS/H_dLnF_dLnF
drop m
drop j
drop a
drop z
drop H_dLnF_dLnS
drop H_dLnF_dLnF
drop H_dLnS_dLnS
}
end
cccGARCH
```

C.2 Matlab

Sharpe hedge ratio

```
hedge_sharpe = zeros(600,1);

for i = 1:600
j = 999 + i;
clear hh sigma_1 sigma_2 rho_12 meanRf mean Rs;
sigma_1 = var(dLnS(i:j)) ^ (1/2);
sigma_2 = var(dLnF(i:j)) ^ (1/2);
rho_12 = corr(dLnS(i:j), dLnF(i:j));
meanRs = mean(dLnS(i:j));
meanRf = mean(dLnF(i:j));
hh = -((sigma_1/sigma_2) * ((sigma_1/sigma_2) * ...
 (meanRf/meanRs) - rho_12))/ (1 - (sigma_1/sigma_2) *...
 (meanRf*rho_12/meanRs));
hedge_sharpe(i) = hh;
end
```

MEG hedge ratio

The first approach:

```
hedge_gini = zeros(600,1);

for i = 1:600
j = 999+i;
meanRs = mean(dLnS(i:j));
meanRf = mean(dLnF(i:j));
vi=1.5;
[vs, vin] = sort(dLnF(i:j));
[x, rank] = sort(vin);
N = size(dLnF(i:j),1);
G = rank ./ N;
y = (1 - G) .^ (vi - 1);
meany = mean(y);
nominator = (dLnS(i:j) - meanRs) .* (y - meany);
denominator = (dLnF(i:j) - meanRf) .* (y - meany);
```

```
hedge = sum(nominator)/sum(denominator);
hedge_gini(i) = hedge;
end
```

The second approach:

```
hedge_gini2 = zeros(600,1);

for i = 1:600
j = 999+i;
gini = zeros(10001,1);

for l = 1:10001;
p = -0.1 + (l - 1) * 0.0001;
meanRs = mean(dLnS(i:j));
meanRf = mean(dLnF(i:j));
return = dLnS(i:j) - p .* dLnF(i:j);
vi=1.5;
[vs, vin] = sort(return);
[x, rank] = sort(vin);
N = size(return,1);
G = rank ./ N;
y = (1 - G) .^ (vi - 1);
gini2 = -vi * sum((return - mean(return)) .* (y - mean(y)));
gini(l) = gini2;
end

hedge = 0.4 + (find (gini == min(gini))- 1) * 0.0001;
hedge_gini2(i) = hedge;
end
```

GSV hedge ratio

```
hedge_GSV = zeros(600,1);

for i = 1:600
j = 999+i;
GSV = zeros(10001,1);
```

```
for l = 1:10001;
clear p delta alpha return N U a GSV2;
p = 0.4 + (l - 1) * 0.0001;
delta = zeros(1000,1);
alpha = 1;
return = dLnS(i:j) - p .* dLnF(i:j);
N = size (return, 1);
cond = delta - return;
U = zeros(1000,1);

for m=1:1000
if (cond(m) < 0)
    U(m) = 0;
else
    U(m) = 1;
end
end

a = ((delta - return) .^ alpha) .* U;
GSV2 = (1/N) * sum(a);
GSV(l) = GSV2;
end

hedge_GSV(i)= 0.4 + (find (GSV == min(GSV))- 1) * 0.0001;
end
```

VaR hedge ratio

```
HR = zeros(20,600);
VAR = zeros(20,600);
OHedge = zeros(1,600);

for i = 1:600
clear solution n m j c a_1 a_2 a_3 a_4 z var h variance...
 variance_2 sk k k_1 k_2 k_a k_b k_c s_1 s_2 s_a s_b ...
 sigma_1 sigma_2 rho_12;
```

```
j = 999 + i;
sigma_1 = var(dLnS(i:j)) ^ (1/2);
sigma_2 = var(dLnF(i:j)) ^ (1/2);
rho_12 = corr(dLnS(i:j),dLnF(i:j));
s_1 = skewness(dLnS(i:j));
s_2 = skewness(dLnF(i:j));
s_a = mean(((dLnS(i:j) - mean(dLnS(i:j))) .^ 2) .* ...
 (dLnF(i:j) - mean(dLnF(i:j)))) / (var(dLnS(i:j)) * ...
 (var(dLnF(i:j)) ^ (1/2)));
s_b = mean((dLnS(i:j) - mean(dLnS(i:j))) .* ...
 (dLnF(i:j) -  mean(dLnF(i:j))) .^ 2) / ...
 (var(dLnF(i:j)) * (var(dLnS(i:j))  ^ (1/2)));
k_1 = kurtosis(dLnS(i:j));
k_2 = kurtosis(dLnF(i:j));
k_a = mean(((dLnS(i:j) - mean(dLnS(i:j))) .^ 3) .* ...
 (dLnF(i:j) - mean(dLnF(i:j)))) / ((var(dLnS(i:j)) ^ ...
 (3/2)) * (var(dLnF(i:j))  ^ (1/2)));
k_b = mean(((dLnS(i:j) - mean(dLnS(i:j))) .^ 2) .* ...
 (dLnF(i:j) - mean(dLnF(i:j))) .^ 2) / (var(dLnF(i:j)) * ...
 var(dLnS(i:j)));
k_c =  mean((dLnS(i:j) - mean(dLnS(i:j))) .* (dLnF(i:j) - ...
 mean(dLnF(i:j))) .^ 3) / ((var(dLnF(i:j)) ^ (3/2)) * ...
 var(dLnS(i:j))  ^ (1/2));

syms h real

variance(h) = sigma_1 ^ 2 + h ^ 2 * sigma_2 ^ 2 - 2 * h * ...
rho_12 * sigma_1 * sigma_2;
variance_2(h) = variance ^ (1/2);
sk(h) = (s_1 * sigma_1 ^ 3 - 3 * h * s_a * sigma_1 ^ 2 * ...
 sigma_2 + 3 * h ^ 2 * s_b * sigma_1 * sigma_2 ^ 2 - h ^ 3 * ...
 s_2 * sigma_2 ^ 3) / (variance ^ (3/2));
k(h) = (k_1 * sigma_1^4 - 4 * h * k_a * sigma_1 ^ 3 * ...
 sigma_2 + 6 * h ^ 2 * k_b * sigma_1 ^ 2 * sigma_2 ^ 2 - ...
 4 * h ^ 3 * k_c * sigma_1 * sigma_2 ^ 3 + h ^ 4 * k_2 * ...
 sigma_2 ^ 4) / (variance ^ 2);
```

```
c=-1.645;

a_1 = c - 1/8 * (c ^ 3 - 3 * c);
a_2 = 1/6 * (c ^ 2 - 1);
a_3 = 1/24 * (c ^ 3 - 3 * c);
a_4 = -1/36 * (2 * c ^ 3 - 5 * c);

z(h) = diff(variance_2, h) * (a_1 + a_2* sk + a_3* k + ...
 a_4* sk ^ 2) + variance_2 * (a_2 * diff(sk,h) + a_3 * ...
 diff(k,h) + 2 * a_4 * sk * diff(sk,h));
var(h)= - variance_2 * (c + 1/6 * (c ^ 2 - 1) * sk + ...
 1/24 * (c ^ 3 - 3 * c) * (k - 3) - 1/36 * (2 * c ^ 3 - ...
 5 * c) * sk ^ 2);
solution = solve(z == 0, h);

if isequal(solution, nil)
    HR(1,i)=999;
    OHedge(1,i)=999;
else
    HR(1:size(solution,1),i) = solution;
    m = size(solution,1) + 1;
    for n=1:m
      VAR(n, i) = var(HR(n,i)) ;
    end
    bb=min(find(VAR(1:m,i)== min(VAR(1:m,i))));
    OHedge(1,i)=HR(bb,i);
end
end
```