Evaluating the Performance of Cotton Future Hedging Strategies in U.S. Market

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Abstract

This paper investigates to what extent a decision-maker in cotton industry can improve performance of operation by hedging. Four hedging strategies (Naïve-Hedge, Simple-OLS, Rolling-over-OLS and CCC-GARCH) under the objective function of minimum variance are examined and compared. In addition, a period-ahead predicted variance is combined above strategies to see whether it can improve the hedging performance of cotton futures. The empirical result indicates that all examined strategies make good performances of reducing the cotton portfolio's variance in U.S. market. While under different objective functions, "minimum variance" and "expected returns", the performances and optimal strategy are different. Furthermore, when strategy is combined the "predicted variance" in advance for making hedge decision, the empirical result is distinctive from above. Finally, Risk aversion level is included into the consideration of optimal hedging strategy.

Key words: Static hedging ratios, Dynamic hedging ratios, Cotton futures, OLS, Bivariate GARCH

Contents

1 Introduction

Cotton is by far the most important natural fibre around the world, although there is a declining trend of cotton's share in textile fibres since the 1970s. Today, cotton is grown in more than 90 countries. China, India, USA and Pakistan were the four main cotton-producing countries in 2006/07 (International Cotton Advisory Committee (ICAC)). The four accounted for approximately three quarters of world cotton production. Additionally, they are the four largest cotton-consumers. According to ICAC (UNCTAD, 2011), China, USA, India, and Pakistan together have accounted for approximately more than 55% of global cotton consumption over the period from1980 to 2008. As the biggest cotton producers as well as consumers, these four countries are more easily affected by the volatility of cotton spot prices than others. Especially in USA, which is also the world's main cotton exporter, the benefits of producers (farmers) and consumers (textile mills) are highly sensitive to the volatility of cotton spot prices. For example, in 2010/11, cotton prices hit their highest levels since the American Civil War (1861-1865). Most of the textile mills (e.g. apparel manufactures) suffered huge losses by the tremendously increasing prices of cotton spot. Contrarily, cotton prices reduced dramatically from April to June of 2011 and that made most of the producers losing a lot.

Historically in United States, the long-term constant-dollar price of cotton has been relatively stable low. However, traders do not use the long-term price of cotton for trade for trade but the short-term current-dollar price of cotton. During the last fifty years, there have been some major trends and sharp reversals in the behavior of short-term price. In other words, short-term price presents high variance. This historic fact tells us in a nutshell why textile mills and cotton farmers need to hedge the price risks, and why cotton futures and options have been so successful over the contracts' lives. Based on the trading volume and open interest of ICE Futures U.S. contracts we can see, cotton future market cannot be ignored not only for its trading opportunities but also for its diversifying properties. Especially after the adoption of electronic trading in 2007, trading volume and open interest started rising higher than ever (ICE, 2007).

However, although the cotton futures have been generally accepted as an effective tool to hedge risks of cotton price volatility (ICE, 2007), but generally the price of cotton is uncertain since its productivity highly depends on climate and weather conditions. Thus, in practice it is hard to correctly predict product's volume and revenue. With this un-predictable limitation, many cotton holders/producers can only choose either 1) trading futures only when the cotton price has substantially changed or 2) making passive hedging strategy (naïve hedge) to reduce risks of the price volatility. The first strategy is in fact a lag-reaction of market performance, even if it does partially reduce the risks, since the price changed in spot market leads the trades in futures market. The second method (naïve hedge) is a strategy that one shorts corresponding units of futures as long as one holds same units of spots. It does reduce risks of the spot price volatility, but it is not the best choice.

Thus, the research questions of this study will be: 1) Can an accurate period-ahead variance forecasting in the spots market help traders of cotton futures to maximize their benefits by adjusting hedging strategies? 2) Can an optimal hedge ratio help to improve the performance of cotton future hedging in U.S. market?

Some articles and papers have turned to examine practicability of "optimal hedge ratio" (Lei &Ko, 1994; Liu et al., 2001). The "optimal ratio" is based on the chosen models and the particular objective function. One of the most widely used objectives is to minimize the variance of hedged portfolio (Johnson, 1960;Stein, 1961). It is simple to understand and estimate. With the objective condition of minimum variance, the most widely used static hedge ratio is the "MV (minimum variance) ratio". Johnson (1960) and Stein (1961) derived this hedge ratio by minimizing the portfolio's variance. Ederington (1979) further demonstrated that under the same objective, the condition of minimizing variance is actually equal to the slope of the simple-OLS regression between the returns of spot and futures. However, "simple-OLS" has an obviously drawback that it ignores variance of spot, variance of futures and covariance of spot and futures are time varying. In other words, static hedge strategy assumes the optimal hedge ratio is fixed and is not revised during the hedging period. The easiest way to allow the hedge ratio to vary is using "rolling-over-sample" in "simple-OLS" estimation, for example, base on week-by-week rolling sample. Bollerslev (1990) announced "CCC-GARCH" that allows a bivariate GARCH process but where the coefficient of correlation between assets is fix over time. Such extending from univariate GARCH models to multivariate GARCH models would definitely increase the number of estimated parameters and the complexity of specifying the conditional variance and covariance matrix. More details are discussed in Engle et al. (1995). Engle (2002) then further proposed "two stages estimation model" that firstly estimates conditional variance and covariance by GARCH, and then estimates "dynamic correlation parameter" by DCC model. The difference between "DCC-GARCH" and "CCC-GARCH" is that DCC allows the correlation coefficient between assets varying over time.

In the following, four different estimating models ("simple-OLS", "Rolling-over-OLS", "CCC-GARCH" and "DCC-GARCH") with "minimum variance" objective condition will be implemented to answer that "Can an optimal hedge ratio help to improve the performance of cotton future hedging in U.S. market?" In addition, since full time hedge could potentially lead to a substantial gain or loss position from hedging, period-ahead predicted variance, which is estimated by univariate-GARCH, will be combined above strategies to examine the cotton hedging performance in U.S. market and to answer the other research question: "Can an accurate period-ahead variance forecasting in the spots market help traders of cotton futures to maximize their benefits by adjusting hedging strategies". Finally, the performances of different hedging strategies with and without accurate variance forecasting will also be compared by using “Variance-reduced Ratio”, “Best performance Times”, “Sharpe Ratio” and “quadratic utility” function.

The outline of the paper is as follows. Section 2 reviews previous studies; section 3 mainly introduces the “optimal hedge ratios” under the objective function of “minimum variance”; section 4 further explains six different hedging strategies with four different estimating tools that are used to derive optimal hedge ratios in this paper; section 5 is the data description and processing; section 6 contains empirical results using the cotton monthly data of spot and futures in U.S. market.

2 Previous Studies Review

Generally, the price of cotton spot is uncertain mostly caused by the unstable supply. Since cotton’s productivity highly depends on climate and weather conditions, in practice it is hard to correctly predict product’s volume and revenue. With this unpredictable limitation, many cotton producers can only choose passive hedging strategy (naïve hedge) to reduce risks of the price volatility. Naïve Hedge is a strategy that one shorts corresponding units of futures as long as one holds same units of spots. It does reduce risks of the price volatility, but it is not the best choice. Some articles and papers have tried to discard so called “naïve hedge” and turned to examine practicability of “optimal hedge ratio” (Lei &Ko, 1994; Liu et al., 2001). The decision of “optimal ratio” is based on the chosen models. There are many theoretical approaches to the optimal future hedge ratios. Simply summarizing, they are based on “minimum variance”, “mean-variance”, “expected utility”, “mean extended-Gini coefficient” and “semi-variance”. Also, there are various ways of estimating hedge ratios, for example “simple ordinary least squares (Simple-OLS)”, “generalized autoregressive conditional heteroskedasticity (GARCH)” and “complicated heteroscedasitc co-integration” methods. According to Chen, Lee &Shrestha (2001), except under martingale and joint-normality conditions, “the optimal hedge ratios based on the different approaches are different and there is no single optimal hedge ratio that is distinctly superior to the remaining ones”.

Undoubtedly, the determination of the optimal hedge ratio is the key theoretical issue in hedging and it depends on the particular objective function, e.g. “minimum variance” or “expected utility”. One of the most widely used approaches is to minimize the variance of hedged portfolio (Johnson, 1960; Stein, 1961). Although simple to understand and estimate, it completely ignores the expected return of the hedged portfolio. In other words this approach assumes individuals are infinitely risk averse. Therefore, other approaches that incorporate both variance and expected return of the hedged portfolio have been proposed (Cecchetti, Cumby &Figlewski, 1988; Howard &D’Antonio, 1984; Hsin, Kuo& Lee, 1994). But in fact if the price of futures follows a pure martingale process (i.e., expected future price change is zero), then the optimal hedge ratio of other objectives will be the same as the ratio of "minimum variance". However, the "mean-variance-based" objective approaches do improve over the "minimum variance" objective approach for them be consistent with the expected utility maximization principle. The disadvantage of this approach is that it requires the use of specific utility function and specific return distribution, which make it much harder and complicated to estimate than "minimum variance" approach.

For eliminating these specific assumptions of return distributions and the utility function, some further approaches have been offered, e.g. minimization of the "Mean extended-Gini (MEG)" coefficient (Cheung, Kwan & Yip, 1990). Interestingly, the "MEG-based" hedge ratio will be the same as the "minimum variance" hedge ratio if the prices are normally distributed (Shalit, 1995). After this, researchers further upgraded hedge ratios approaches to those based on the "generalized semi-variance (GSV)" or "lower partial moments" (Chen, Lee &Shrestha, 2001; De Jong, De Roon& Veld, 1997; Lien &Tse, 1998, 2000). These hedge ratios are not only consistent with the concept of stochasticity, but also consistent with the risk perceived by managers because of its emphasis on the returns below the target return. Lien &Tse (1998) show the "minimum-GSV" hedge ratio will be equal to the "minimum variance" hedge ratio when the spots and futures returns are jointly normally distributed and futures price follows a pure martingale process. Most of the above studies ignore transaction costs and investments in other financial assets. Lence (1995, 1996) derives the optimal hedge ratio with transaction costs and investment in other financial assets in the model and finds that under certain circumstances, the optimal hedge ratio is zero.

As it is known, the optimal hedge ratios not only depend on particular objective functions, but also relate to the ways of estimating. Thus, another key theoretical issue in hedging is difference in terms of the dynamic nature of the hedge ratio. Some studies assume that the hedge ratio is constant over time. These so called "static hedge ratios" are estimated using unconditional probability distributions (Benet, 1992; Ederington, 1979). On the other hand, many other studies believe the hedge ratio change over time. In contrast to "static hedge ratios", the so called "dynamic hedge ratios" are estimated using models based on conditional distributions such as "autoregressive conditional heteroskedasticity (ARCH)" and "generalized autoregressive conditional heteroskedasticity (GARCH)". In practice, there are many available techniques that employed for estimating optimal hedge ratios, ranging from simple (e.g. ordinary least squares OLS) to complex ones, for example the conditional heteroscedasitc, ARCH or GARCH (Baillie & Myers, 1991), Random Coefficient Method (Grammatikos& Saunders, 1983), Co-integration Method (Ghosh, 1993) and Co-integration-heteroscedasitc Method (Kroner & Sultan, 1993).

3 Methodology: Optimal hedge ratios under the objective function of minimum variance

Future contract is one of the most popular and acceptable hedging tools. Since spot and futures prices are moving toward the same direction, so it is possible to make an opposite positions of spot and futures (by spot and future markets) in the same time. As the result, positive earning in futures market can offset any loss that is caused by price volatility in spot market. This combined investments in the spot and futures markets to form a portfolio is assumed to reduce value fluctuations of the spot.

In this paper, cotton monthly data in U.S. market from Jan. 1986 to Apr. 2011 is used to examine alternatives hedging strategies. If let S_t and F_t denote cotton spot and futures prices at time t, $R_{st} = (S_t - S_{t-1}) / S_{t-1}$ and $R_{ft} = (F_t - F_{t-1}) / F_{t-1}$ are so called one-period returns on cotton spot and futures. Considering a specific cotton portfolio that consists of units of long position in spot and units of short position in futures. The return of the hedged portfolio R_P can be expressed as:

$$R_p = R_{st} - hR_{ft} \qquad (3.0)$$

where h is so called the hedge ratio. The extensive literature on the issue of hedging with futures denotes the interest to the subject by both scholars and practitioners.

Choosing the optimal hedge ratio is the main objective of hedging. As mentioned above, the optimal hedge ratio depends on a particular objective function to be optimized. In addition, it can be static or dynamic ratios. In section 3.1 and section 3.2, static and dynamic hedge ratios under the objective function of minimum variance will be discussed respectively.

3.1 Static Hedge Ratios

With the objective condition of minimum variance, the most widely used static hedge ratio is the “MV (minimum variance) ratio”. Johnson (1960) and Stein (1961) derived this hedge ratio by minimizing the portfolio risk, or portfolio’s variance. Ederington (1979) further demonstrated that under the minimum variance objective, the condition of minimizing variance is actually equal to the slope of the simple-OLS regression between the returns of spot and futures prices. In addition, he also pointed out that optimal hedge ratio that derived under minimum-variance objective is actually the same as the one under maximum-utility objective. Specifically, the variance of changes value of the hedged portfolio can be expressed as:

$$Var(R_h) = Var(R_s) - 2hCov(R_s, R_f) + h^2 Var(R_f) = \sigma_s^2 - 2h\rho\sigma_s\sigma_f + h^2\sigma_f^2 \quad (3.1)$$

where, σ_s and σ_f are the standard deviations of R_s and R_f , ρ is the correlation parameter between R_s and R_f , h is the estimated optimal hedging ratio. Although in practice operation process, there are two different positions: Short or Long. But the variances of them are actually the same. Thus, the first difference of $Var(R_h)$ can be seen as the optimal hedge ratio: $h^* = \rho(\sigma_s / \sigma_f)$. In practical, we can easily use "simple-OLS" regression model $r_{s,t} = \phi + \varphi r_{f,t} + \varepsilon_t$ to estimate parameter $\hat{\varphi}$, where $r_{s,t} = 100 \times \ln(S_{st} / S_{st-1})$ and $r_{f,t} = 100 \times \ln(S_{ft} / S_{ft-1})$ are the daily returns of cotton spot and futures in percent. $\hat{\varphi}$ is just the optimal hedge ratio and it is a fix constant within the estimation interval.

3.2 Dynamic Hedge Ratios

Although the "simple-OLS" model is generally accepted as one of the most efficient estimation tools, but it has limitation. The most obviously drawback is that it ignores the variances and covariance of spot and futures are time varying. In other words, static hedge strategy assumes the optimal hedge ratio is fixed and is not revised during the hedging period. However, it could be beneficial to allow the hedge ratio changing over time. The easiest way to allow the hedge ratio to vary is by using "rolling over-sample" in "simple-OLS" estimation, for example based on week-by-week rolling sample, then the optimal hedge ratio $\hat{\varphi}$ will be time varying.

Other ways to allow the hedge ratio to change is by re-estimating optimal hedge ratio based on the conditional information on variance (σ_f^2) and covariance (σ_{sf}). Thus, the optimal hedge ratio then turns to be calculated by:

$$h^* \mid \Omega_{t-1} = \frac{\sigma_{sf} \mid \Omega_{t-1}}{\sigma_f^2 \mid \Omega_{t-1}} \quad (3.2.1)$$

The optimal hedge ratio based on conditional information can be implemented by using conditional models such as GARCH. In 1982, Engle proposed ARCH modeling to capture the time varying volatility in time series. It assumes the variance of the current error term or innovation to be a function of the actual sizes of the previous time periods' error terms. In other words, ARCH models the conditional as the squares of the previous innovations, so it is commonly employed in modeling financial time series that exhibit time-varying volatility clustering. Bollerslev (1986) further expanded ARCH model to GARCH model. In this case, GARCH includes "autoregressive moving average model" (ARMA model) in the error variance. This improvement makes the dynamic structure of conditional variances more general and estimated parameters more correctly. Later on, more and more studies further expand GARCH model's concept to asset's co-variance matrix, which allows co-variance matrix varying with time. As the result, there comes out “multivariable GARCH model family”, for example estimating by DCC, VECH and BEKK model. Although all these three models can depict characteristic of time varying co-variance, but in actual operation, they are much harder to be employed. Myers and Thompson (1989) and Bollerslev (1990) extended the univariate GARCH model to bivariate GARCH models with time varying conditional variance and covariance, but constant conditional correlation. This so-called CCC-GARCH bivariate structure model significantly simplifies the estimation procedures. In this case, the conditional variance and covariance from the GARCH model are used to estimate the optimal hedge ratio. The estimation process is given by:

$$\begin{bmatrix} R_{st} \\ R_{ft} \end{bmatrix} = \begin{bmatrix} \mu_s \\ \mu_f \end{bmatrix} + \begin{bmatrix} \varepsilon_{st} \\ \varepsilon_{ft} \end{bmatrix} \Leftrightarrow R_t = \mu + \varepsilon_t, \qquad (3.2.2)$$

$$\varepsilon_t \mid \Omega_{t-1} \sim N(0, H_t), H_t = \begin{bmatrix} H_{11,t} & H_{12,t} \\ H_{12,t} & H_{22,t} \end{bmatrix}, \qquad (3.2.3)$$

$$vec(H_t) = C + Avec(\varepsilon_{t-1}\varepsilon_{t-1}^{'}) + Bvec(H_{t-1}). \qquad (3.2.4)$$

So, the conditional optimal hedge ratio at time t will then given by:

$$h^* = H_{12,t} / H_{22,t} = \frac{\mathrm{cov}(R_{st}, R_{ft})}{\mathrm{var}(R_{ft})} \qquad (3.2.5)$$

Engle (2002) further proposed “two stage estimate model”, which firstly estimates conditional variance and covariance by GARCH in the first stage, and then further estimate “dynamic correlation parameter” with previous estimated variables in the second stage. The different between this method and “CCC-GARCH” (Myers and Thompson, 1989;Bollerslev, 1990) is that it allows the coefficient correlation between assets varying over time. This so-called “DCC-GARCH” model can estimate the optimal hedged ratios by multiplying varying parameter ρ_t to varying variances of spot and futures (σ_{st} and σ_{ft}). With this advanced method, the optimal hedge ratio is given by:

$$\begin{bmatrix} R_{st} \\ R_{ft} \end{bmatrix} = \begin{bmatrix} \mu_s \\ \mu_f \end{bmatrix} + \begin{bmatrix} \varepsilon_{st} \\ \varepsilon_{ft} \end{bmatrix} \Leftrightarrow R_t = \mu + \varepsilon_t, \qquad (3.2.6)$$

$$\varepsilon_t \mid \Omega_{t-1} \sim N(0, H_t), H_t = \begin{bmatrix} H_{11,t} & H_{12,t} \\ H_{12,t} & H_{22,t} \end{bmatrix}, \qquad (3.2.7)$$

$$vec(H_t) = C + Avec(\varepsilon_{t-1}\varepsilon_{t-1}^{'}) + Bvec(H_{t-1}), \qquad (3.2.8)$$

$$\begin{bmatrix} H_{ss,t} & H_{sf,t} \\ H_{sf,t} & H_{ff,t} \end{bmatrix} = (1-a-b)\begin{bmatrix} 1 & \bar{H}_{sf} \\ \bar{H}_{sf} & 1 \end{bmatrix} + a\begin{bmatrix} \varepsilon_{s,t-1}^2 & \varepsilon_{sf,t-1} \\ \varepsilon_{sf,t-1} & \varepsilon_{f,t-1}^2 \end{bmatrix} + b\begin{bmatrix} H_{ss,t-1} & H_{sf,t-1} \\ H_{sf,t-1} & H_{ff,t-1} \end{bmatrix}. \qquad (3.2.9)$$

Where, R_{it} represents $N \times 1$ vector of asset's returns; I_{t-1} is the collection of all the relative information that will affect asset's returns up through time $t-1$; H_t is the co-variance matrix of assets' returns and can be separated as correlation parameters matrix times two conditional standard deviation matrixes; h_{it} for $i = S \,\&\, F$ is the variance (σ_{it}^2) of the i th asset; A, B are the vectors of estimated parameters of i th asset in GARCH model; a, b are the estimated parameters of DCC model. Besides, if N assets' returns are all stable fitted with GARCH model, since R is positive definite, so covariance of assets' return H_t is surely positive definite, which means DCC model is positive definite.

4 Alternatives hedging strategies with different estimating models under the objective function of minimum variance

4.1 Naïve Hedge Strategy (Static hedge ratio)

In the case for which cotton spot exposure is hedged every single period, then this so called "naïve hedge". Specifically, shorting 1 unit of futures when holding 1 unit of spot in every time t for all evaluation periods without taking into consideration the level of hedging required. Consequently, the risk of cotton spot prices volatility is eliminated completely. The Return that the trader gains for this strategy is the difference between returns of spot and futures. The naïve hedge process is given by:

$$R_p^{naive} = R_s - h^{naive} R_f, h^{naive} = 1 \qquad (4.1)$$

Although it is easy to operate in practical work, naïve hedge in other hand could potentially lead to a substantial gain or loss position from hedging.

4.2 Simple OLS Strategy (Static hedge ratio)

Johnson (1960) derived the optimal hedged ratio under the objective function of minimum variance. The expressions of long and short positions in futures are given by $R_h = hR_f - R_s$ and $R_h = R_s - hR_f$ respectively. Then the variance of either long or short position is given by equation (3.1)

$$Var(R_h) = Var(R_s) - 2hCov(R_s, R_f) + h^2 Var(R_f) = \sigma_s^2 - 2h\rho\sigma_s\sigma_f + h^2\sigma_f^2$$

where, R_s and R_f are changes in the logarithm prices of spot and future, σ_s and σ_f are the standard deviation of R_s and R_f, ρ is the correlation parameter of R_s and R_f, h is the estimated optimal hedged ratio. As that have been discussed in section 3.1, the first difference of $Var(R_h)$ can be seen as the optimal hedged ratio: $h^* = \rho(\sigma_s / \sigma_f)$.
The "simple-OLS" estimation process is given by:

$$r_{s,t} = 100 \times \ln(S_{st} / S_{st-1}) \qquad (4.2.1)$$

$$r_{f,t} = 100 \times \ln(S_{ft} / S_{ft-1}) \qquad (4.2.2)$$

$$r_{s,t} = \phi + \varphi r_{f,t} + \varepsilon_t \qquad (4.2.3)$$

where, the estimated parameter $\hat{\varphi}$ is then the optimal hedge ratio h^*. Thus, the optimal hedge ratio is then be fixed at a constant level. Specifically in practice is shorting $\hat{\varphi}$ units of futures for all time t in evaluation periods wherever prices go. The return that trader gains is given by:

$$R_{pt}^{sOLS} = R_{st} - h^* R_{ft}, h^* = fix \qquad (4.2.4)$$

4.3 Rolling-over-OLS Strategy (Dynamic hedge ratio)

As that have been discussed in section 3.2, "Rolling-over-OLS" can be an easier way to solve the limitation of "simple-OLS". This means that "Simple-OLS" does not allow the parameter of optimal hedge ratio to change over time. In this case, fix sample is replaced with month-by-month rolling sample, and estimated time varying optimal hedge ratio by running OLS regression. The varying optimal hedge ratio that depends on latest information then can be taken to hedge risks of the cotton spot price. Likewise the above strategy, spot is hedged with $\hat{\varphi}$ units of futures for all time t. The return of this portfolio is given by:

$$R_{pt}^{rOLS} = R_{st} - h_t^* R_{ft}, h_t^* = nonfix \qquad (4.3)$$

4.4 CCC-GARCH Strategy (Dynamic hedge ratio)

Except "rolling-over-OLS" strategy, CCC-GARCH model is another efficient way to deal with the limitation of "simple-OLS". Compared to "Rolling-over-OLS", CCC-GARCH estimation is a more precise and intuitive method. With the estimated conditional variance and covariance at each time t, we then can recalculate the estimated optimal hedge ratio from "Rolling-over-OLS" model. The process is given by:

$$h_t^* = \rho \frac{\sigma_{st}}{\sigma_{ft}} = \frac{\rho \sigma_{st} \sigma_{ft}}{\sigma_{ft}^2} = \frac{\operatorname{cov}(R_s, R_f)}{\operatorname{var}(R_f)} \qquad (4.4.1)$$

As we see from equation (4.4.1), in practice we do not need to run "Rolling-over-OLS" but only calculate the optimal hedge ratio by dividing covariance of spot and futures with variance of futures. Again, h_t^* units of futures are shorted at every time t for the whole evaluation period. The return of hedged portfolio is given by:

$$R_{pt}^{garch} = R_{st} - h_t^* R_{ft}, h_t^* = nonfix \qquad (4.4.2)$$

Although CCC-GARCH relieves the limitation of time varying variance and co-variance in Simple-OLS estimation model, but in other hand it has its own shortage: CCC-GARCH assume the correlation coefficient parameter between assets (e.g. spot & futures) is constant. It ignores correlation parameter's nature of time varying that may affect the performance of hedged decision in a certain level.

4.5 DCC-GARCH Strategy (Dynamic hedge ratio)

DCC-GARCH model further frees assumptions/limitations of CCC-GARCH model. It allows the correlation coefficient between assets varying over time. In this case, conditional variance and covariance are firstly estimated by GARCH in the first stage, and then "dynamic correlation parameter" is estimated with previous estimators in the second stage. Then the optimal hedge ratios is given by:

$$h_t^* = \rho \frac{\sigma_{st}}{\sigma_{ft}} = (1 - a - b) \frac{\sigma_{st}}{\sigma_{ft}} \qquad (4.5.1)$$

Hedging risk of cotton spot volatility by shorting h_t^* units of futures at each time t for over evaluation period, we then gain return as:

$$R_{pt}^{DCC} = R_{st} - h_t^* R_{ft}, h_t^* = nonfix \qquad (4.5.2)$$

4.6 Improvement Strategy with Predicted Variance

So far, all of the discussed hedging strategies can reduce variance of hedged portfolio. In the other hand, they can also harm the returns of portfolio in a certain level. Specifically, full time hedge could potentially lead to a substantial gain or loss position from hedging. Obviously, this potential risk is just the shortage of minimum variance subjective: it does not consider expected returns. There is an easy and intuitive way to reduce the harm on returns in a certain level (but of course not the best). That is using predicted variance in advance to decide whether to take hedging action before doing any hedging action. More specifically, a period-ahead predicted variance of cotton spot return ($\sigma^2_{s,t+1}$) is set as a target. Once $\sigma^2_{s_{t+1}}$ is larger than σ^2_{st} (current variance of spot return), then h^* or h^*_t units of futures can be shorted in the market to hedge risks in spot market. If $\sigma^2_{s_{t+1}}$ is smaller or equal to σ^2_{st} , then no action will be taken. This strategy process is given by:

$$
\begin{aligned}
&\sigma^2_{s_{t+1}} > \sigma^2_{s_t} \rightarrow h = \begin{cases} h^*, & static \\ h^*_t, & dynamic \end{cases} \\
&or \qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad (4.6.1) \\
&\sigma^2_{s_{t+1}} \le \sigma^2_{s_t} \rightarrow h = 0
\end{aligned}
$$

As combined this pre-treatment of hedging decision, then all above-mentioned strategies can simply incorporate both the objective functions of minimum variance and expected returns. In practice they can partially reduce the potential losses on hedged portfolio although they also partially increase portfolio's variances. However, this is indeed a trade-off between two objectives. For choosing best strategy, we need to further consider individual's risk aversion level.

4.7 Quadratic Utility Function

Preference for a high mean return and a low variance of portfolio return is called "mean-variance framework". When doing trade-off between these factors in a linear function, it is necessary to maximize a linear combination of the two with positive coefficient on the mean and a negative coefficient on the variance. The expression is:

$$U = r_p - \frac{A}{2} * \sigma^2_p \qquad (4.7.1)$$

where U is the expected utility, r_p is the expected return of portfolio and σ^2_p is the variance of portfolio return. The parameter A is the risk aversion coefficient and the "2" is there for mathematical convenience. In financial economics, this is the most frequently used utility function. In this paper, it will be used to measure alternatives hedging strategies as well as to choose the optimal strategy.

5 Data Description and Processing

5.1 Basic Description of Data

My data set consists of daily observations on the cotton spot & futures prices in U.S. market for the period 1981-1-31 until 2011-4-12, which gives a total of 6573 observations both for spot and futures. All data come from Datastream. In Datastream, there are lots of price resources can be found. In this paper, "Cotton, 1 1/16Str Low - Midl, Memph C/Lb (~U$)" and "Cotton NY Future Cents/lb (~U$)" has been chosen since they are representative of "Cotton Trading" with relatively high trading volumes.

In the upper panel of Figure 1 the time series are presented in levels and in first differences of the logarithms for the whole period of cotton spot prices. To be worth to mention, the prices in levels are current prices that include inflation effect. Specifically in this case, according to U.S. Consumer Price Index (CPI), in 1982 one could purchase an item (e.g. cotton) for 1 U.S. dollar but today in 2011 it costs 2.34 U.S. dollar. The rate of inflation change has been 134.1%.

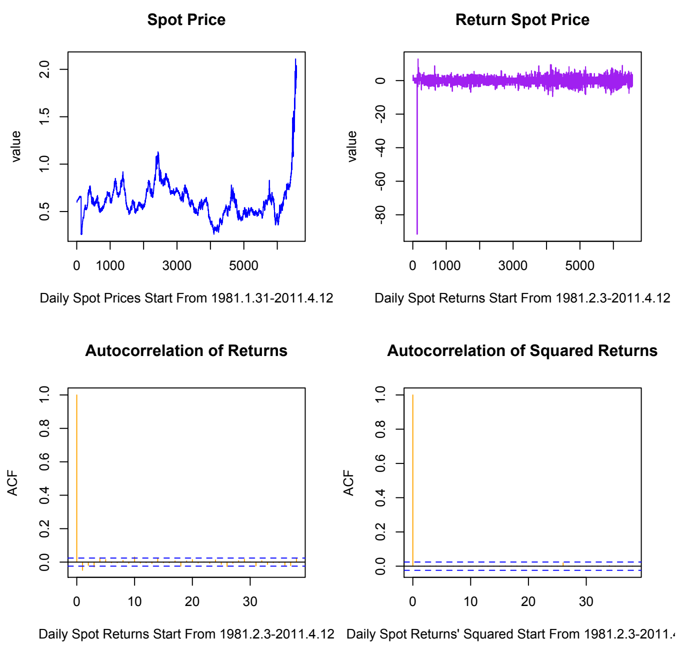


Figure 1: Levels and returns of cotton spots

In the lower panel is the autocorrelation function of the returns and the squared returns, which do not show clear serial correlation. They exhibit patterns frequently found in high frequency financial return data. This corroborates the widely held view that financial return series are unpredictable.

The upper panel of Figure 2 is the levels and returns of cotton futures prices for the whole period. The lower panel of Figure 2 is the autocorrelation function of the returns and the squared returns, which do not show clear serial correlation either.

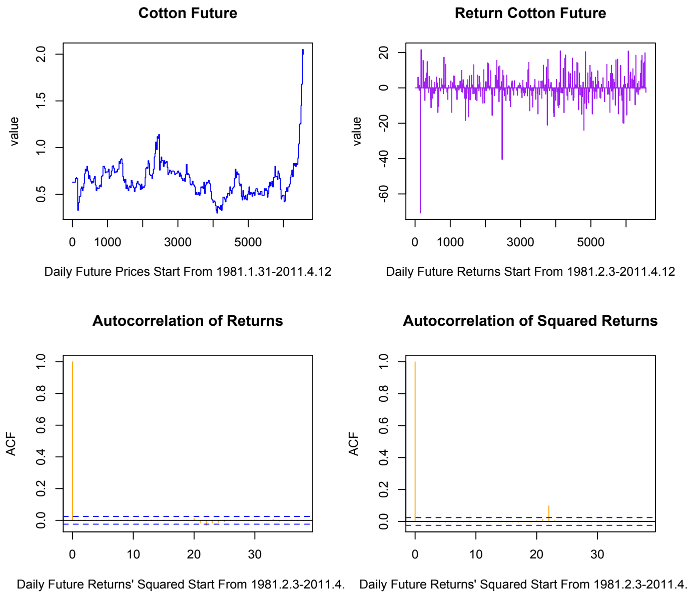


Figure 2: Levels and returns of cotton futures

From Figure1 and Figure 2 we can roughly see that the frequency of cotton futures is not as high as spot and the volatilities of futures returns are larger than that of spot returns. However, in the Figure3 that includes both cotton spot and futures prices in level, we can see prices' trends are mainly the same although they fluctuate in different levels.

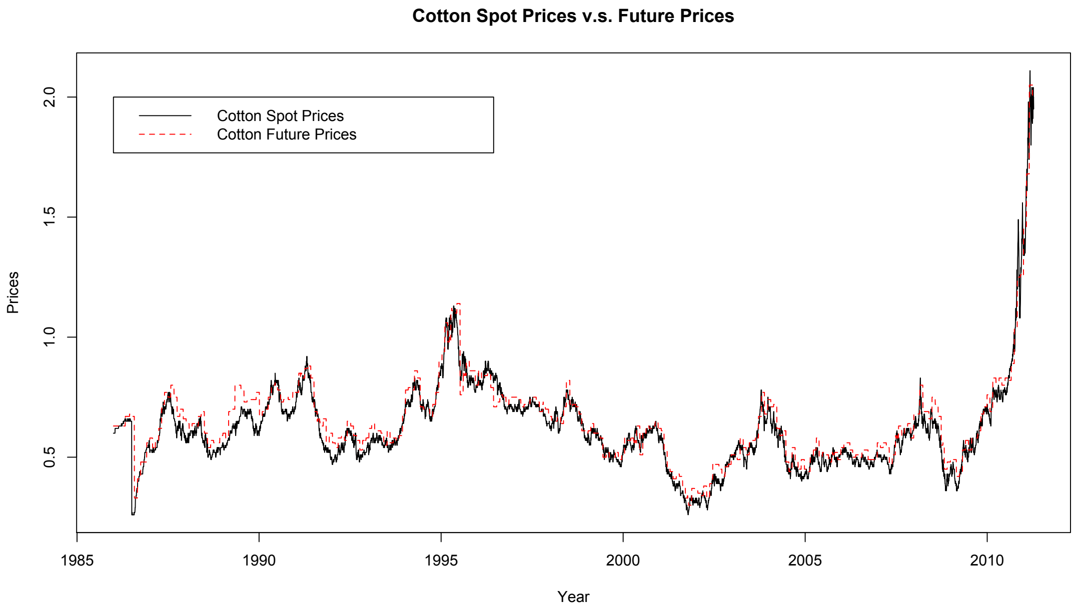


Figure 3: Cotton spot prices vs. futures prices

Examining the correlation coefficient parameter between spot and futures returns can further learn this fact of "trending in same way but fluctuating in different levels". Table 1 presents the parameters of cotton spot returns vs. futures returns with three different time frequency data. Based on Table 1 as well as above figures, we can see that in the long run (or under lower frequency), cotton spot and futures returns are highly correlated to each other. The correlation coefficient parameter turns larger when data frequency goes lower. Thus in this case, using lower frequency data will be more meaningful since only highly correlation assets can be used to hedge risk. In this paper, cotton monthly data in U.S. market from Jan. 1986 to Apr. 2011 is used to examine alternatives hedging strategies.

Table 1 Cotton spot returns vs. future returns

Cotton spot returns vs. futures returns			
	Daily data	**Weekly data**	**Monthly data**
Correlation Coefficient	0.04396	0.1153	0.85694
t-value	(-3.353)	(-4.244)	(-26.061)
Pr(>|t|)	0.000805 ***	2.35e-05 ***	<2e-16 ***

5.2 The Description of Basic Statistics

As we can see in the Table 2, neither Spot Level Prices nor Futures Level Prices follow the normal distribution. In addition, the Kurtosis values of both Spot & Future are large higher than 3, which mean both of them have fat-tails. This characteristic can also be seen in Figure4 and Figure 5 (in Appendix).

Table 2 Basic Statistics of cotton Spot & Futures monthly prices

Cotton Monthly Spot & Futures Level Prices from 1986.1-2011.4									
	Min.	**1st Qu.**	**Median**	**Mean**	**3rd Qu.**	**Max.**	**Standard Deviation**	**Skewness**	**Kurtosis**
Spot	**0.27**	**0.51**	**0.6**	**0.6243**	**0.7**	**2.09**	**0.2012834**	**2.911742**	**18.87164**
Future	**0.3**	**0.54**	**0.63**	**0.6544**	**0.74**	**2.05**	**0.2012704**	**2.939699**	**18.79852**

Table 3 describes the basic statistics of Cotton Spot & Futures Returns. The same as the results in Table 2, both Spot and Future Returns do not follow normal distribution.

Table 3 Basic Statistics of cotton Spot & Futures monthly returns

Cotton Monthly Spot & Futures Returns from 1986.1-2011.4									
	Min.	**1st Qu.**	**Median**	**Mean**	**3rd Qu.**	**Max.**	**Standard Deviation**	**Skewness**	**Kurtosis**
Spot	**-87.855**	**-4.7628**	**0**	**0.3874**	**5.2842**	**39.3043**	**9.870372**	**-2.100419**	**23.8042**
Future	**-70.819**	**-4.1385**	**0**	**0.3838**	**5.4067**	**21.7065**	**9.597679**	**-1.499214**	**13.0521**

5.3 Data Processing

All the above figures and basic statistic information of sample data clearly show that neither cotton spot nor futures are normally distributed and stationary. In addition, with the high kurtosis in both cotton spot and futures returns, there could be outlier effect. Next, the sample data will be further processed by examining the outlier and monthly trend.

5.3.1 Excluding Outliers

According to outliers' effect examination, during September 1986 cotton spot returns plumbed down to 0.27. This is mainly caused by the super increment of cotton output and the high storage rate (53.21%) that was published by U.S. government at the end of 1985. Eliminating this data point results that data becomes much nicer behaved.

Figure 6 (in Appendix) is the density of cotton spot and futures before and after excluding outliers, and Figure 7 (in Appendix) is the pattern of spot and futures series before and after excluding outliers. It is clearly to see that by excluding outliers in these two series, returns of spot and futures are more normally distributed.

5.3.2 Examining Monthly Trends and Simple Mean-adjusted

The purpose of de-trending spot and future prices variables is to separate long run growth and monthly variations from cyclical (and random) phenomena. Denote S_{st} and S_{ft} as the monthly price index of spot and futures cotton, and define $r_{s_t} = 100 \times \ln(S_{s_t} / S_{s_{t-1}}), r_{f_t} = 100 \times \ln(S_{f_t} / S_{f_t})$ as the percent daily return on a continuously compounding basis. Since the sample is monthly data, so I assume that the mean equation of the return is captured by 12 dummy variables representing different expected returns for various months of the year. In addition, the residues follow an autoregressive process of order h.

$$r_{s_t} = \alpha + \mu_{2s} D_{2s_t} + \mu_{3s} D_{3s_t} + \mu_{4s} D_{4s_t} + \mu_{5s} D_{5s_t} + \cdots + \mu_{12s} D_{12s_t} + u_{s_t}$$
$$r_{f_t} = \alpha + \mu_{2f} D_{2f_t} + \mu_{3f} D_{3f_t} + \mu_{4f} D_{4f_t} + \mu_{5f} D_{5f_t} + \cdots + \mu_{12f} D_{12f_t} + u_{f_t}$$

and

$$u_{s_t} = \sum_{k=1}^{h} \theta_{sk} u_{s_{t-k}} + \varepsilon_{s_t}, u_{f_t} = \sum_{k=1}^{h} \theta_{fk} u_{f_{t-k}} + \varepsilon_{f_t}$$

where, D_{tj} for $j = 2,\cdots,12$ are the dummy variables with value 1 if the return is on the j th month of year and value 0 otherwise. Hence, μ_{ij} for $i = s \,\&\, f, j = 2,.\cdots,12$ represent the expected return of the j th month of year. Also, u_{s_t} & u_{f_t} are the residues and θ_{ik} are the parameters of autoregressive.

Table 4 is the summary of the estimation results of the mean-adjusted equations. The monthly effect is represented by the estimated values of $D_1,\cdots,D_{12}$. None of them are significantly different from zero at the 5% level. Thus the conclusion is that there are no monthly trends both in cotton spot and futures returns.

Table 4 Summaries of Mean-Adjusted Equations

Summaries of Mean-Adjusted Equations						
Dummy Variables	**SPOT**			**FUTURES**		
	Estimate	**t value**	**Pr(>|t|)**	**Estimate**	**t value**	**Pr(>|t|)**
Intercept	1.31216	0.78	0.4353	1.8266	1.048	0.296
D2	-0.29820	-0.126	0.9002	-1.7975	-0.729	0.467
D3	-2.46392	-1.037	0.3005	-3.9102	-1.586	0.114
D4	-2.85636	-1.202	0.2302	-3.0223	-1.226	0.221
D5	-4.25555	-1.792	0.0743 .	-2.6326	-1.068	0.287
D6	0.67978	0.286	0.7749	-0.7600	-0.308	0.758
D7	-0.20653	-0.087	0.9308	-0.8776	-0.356	0.722
D8	0.66376	0.279	0.7801	2.1328	0.865	0.388
D9	-0.02863	-0.012	0.9904	-0.5909	-0.240	0.811
D10	3.48411	1.467	0.1435	0.1612	0.065	0.948
D11	-2.46307	-1.037	0.3006	-2.2422	-0.909	0.364
D12	0.06874	0.029	0.9772	-0.8895	-0.357	0.721

Figure 8 (in Appendix) is the auto-correlation and partial auto-correlation functions of the mean adjusting series of spot and futures returns. Both cotton spot and futures do not exhibit significant serial correlation in their returns. Obviously seeing from Figures 7&8, the two "outliers excluding" and "mean-adjusting" series are now more stationary and normally distributed.

6 Empirical Results and Discussion

For all hedging strategies in this paper, data from Jan. 1986 to Dec. 2008 is assumed as "current available information" and dates from Jan. 2009 to Apr. 2011 is the evaluation periods. In the performances evaluation process, the real data of cotton spot and futures returns will be used to calculate the variances and returns of both hedged and un-hedged portfolio for each strategy.

Unfortunately, when running DCC-GARCH with data sample, it could not get consistent “meaningful” parameters for every estimation period from Jan. 2009 to Apr. 2011. Perhaps this is a “hard” period due to financial turmoil and several nature catastrophes. The estimated parameters are very sensitive to the initial parameters that were used in iteration estimating process. This may be mainly caused by the complexity of dynamic correlation coefficient GARCH. One possible reason is that my data set is not large enough to make estimation in DCC-GARCH model. Normally, DCC model is most useful for long time series whereas time series below 100 time-points remain challenging. The other possible cause is that there is no dynamic coefficient correlation between cotton spot and futures. Their correlation is fix over time.

Residual returns of mean-adjusted equations are employed to estimate the Simple-OLS, Rolling-over-OLS and CCC-GARCH models. The results are summarized in Table 5.

Table 5 Estimation Results

Estimation Results								
Models	**Simple-OLS**	**Rolling-Over-OLS**	**CCC-GARCH (SPOT)**			**CCC-GARCH (FUTURE)**		
	Coefficient	Coefficient	Intercept	Alpha	Beta	Intercept	Alpha	Beta
Estimates	0.74861	0.7486137	59.81	0.1025	9.18E-13	65.45	0.0997	3.409E-13
t-value	20.654	20.654	1.562	1.55	1.28E-12	1.969	1.193	6.95E-13
Pr(>|t|)	<2e-16 ***	<2e-16 ***	0.177	0.121	1	0.0489 *	0.2329	1

Note: The sample interval is 1986/1-2011/4, a total of 301 monthly observations. Rolling sample is implemented to estimate a total of 28 out of sample observations in this paper. These are the first out of sample estimated parameter.

6.1 Variance Performances of Hedging Strategies

For measuring the performances of different hedging strategies, there are many available choices. Cotter and Hanly (2006) listed 5 performance evaluation methods that based on “variance”. They pointed out that the choice of performance evaluation should be based on the research objective. Since in this paper, the focus is on comparing the performances of different hedging strategies and they are all based on “minimum variance” objective condition, thus “Variance-reduced Ratio” index is chosen as the measure tool. This intuitive method is one of the most popular ones. It calculates the reduced-variance ratio of hedging strategy by comparing the variances of hedged and un-hedged portfolios. The calculation formula is given as: $1-[Var(P_{Hedged})/Var(P_{Unhedged})]$. Table 6 is the results of performances in “Variance-reduced Ratio”.

Table 6 Variance reduced ratios

Variance Reduced Ratio of alternatives Hedging Strategies (Average of Jan. 2009 – April. 2011)				
Condition	**Naïve Hedge**	**Simple-OLS**	**Rolling-over OLS**	**CCC-GARCH**
Without Predicted Variance	0.18116503	***0.31501909***	0.313084251	0.31405341
With Predicted Variance	0.10524877	0.18120239	0.179999743	***0.18155068***

From Table 6 we can see:

1). All hedge strategies effectively reduced variance of cotton spot;

2). Strategies that without predicted variance in advance to decide whether to hedge played much better than that with predicted variance. The "variance-reduced ratios" of the former one are around 31% and the ratios of the later one are around 18% except "Naïve Hedge";

3). If only seeing strategy that without predicted variances filter, Simple-OLS has highest reduced ratio 31.50%, although CCC-GARCH has a very closed one 31.41%;

4). If only seeing strategy that with predicted variances filter, CCC-GARCH performs best with ratio of 18.16%, but Simple-OLS also has a very closed ratio 18.12%;

5). No matter what strategy, with or without predicted variances, Rolling-over OLS is worse than Simple-OLS even though their ratios are close to each other. This result contradicts to my primary expectation and to some previous studies: e.g. Wu, Liu, & Yang (2009). In Wu, Liu, & Yang (2009)'s paper, they demonstrated that Rolling-over OLS and CCC-GARCH played better than simple-OLS, especially for CCC-GARCH. Two possible reasons may cause this in-consistent results: (a) Short periods of evaluation: The evaluation periods in this paper range from Jan of 2009 to April of 2011 with totally 28 out of sample hedging performances, and in the other paper the evaluation periods started from 2000/1/3-2006/12/29 with totally 365 out of sample hedging performances. Simple-OLS probably works in period where price goes in one direction either up or down. As with short periods of evaluation is more likely to have a more single trend. Thus, Simple-OLS works better than others; (b) Data frequency is different: In this paper I use cotton-monthly spot and futures returns as examination sample but in (Wu, Liu, & Yang, 2009) they did research on weekly data.

Only based on above information, it is hard to say which strategy outperforms the other one. To be more completed, the "best performance times" of all strategies for the whole evaluation periods have been collected in Figure 9.

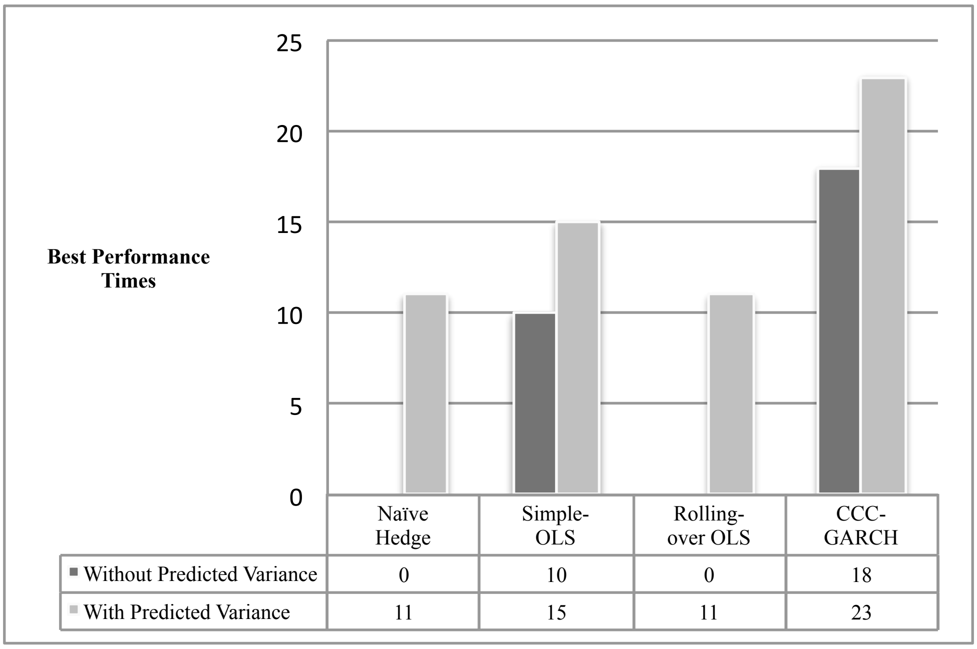


Figure 9: Variance reduced ratios of alternatives hedging strategies: Best performance times

As we can see from it, CCC-GARCH's best performance times are larger than all the other strategies no matter with or without predicted variance filter. Simple-OLS is the second performer. Thus, taking all the above stated, one can argue that, "CCC-GARCH without predicted variance filter" is the best choice for hedging risks of the cotton spot price volatility if only considering "minimum variance" objective.

6.2 Returns Performances of Hedging Strategies

As that have been discussed in section 1 and section 2, although "minimum variance" objective condition is simple to understand and estimate but it completely ignores the expected return of the hedged portfolio. In other words this strategy assumes individuals are infinitely risk averse. Thus we cannot easily say that "CCC-GARCH without predicted variance filter" is the best performer if only includes "minimum variance" in consideration. Table 7 is the returns performances of different hedging strategies in average, and also Figure10 is the "best performance" times of different hedging strategies with returns.

Table 7 Returns of alternatives hedging strategies

Returns of alternatives Hedging Strategies (Average)					
Condition	**Un-Hedged**	**Naïve Hedge**	**Simple-OLS**	**Rolling-over OLS**	**CCC-GARCH**
Without Predicted Variance	5.583549907	0.48670578	1.768001425	1.730130274	1.868345432
With Predicted Variance	5.583549907	1.424662081	2.470164891	2.441913023	***2.539200551***

From Table 7 we can see:

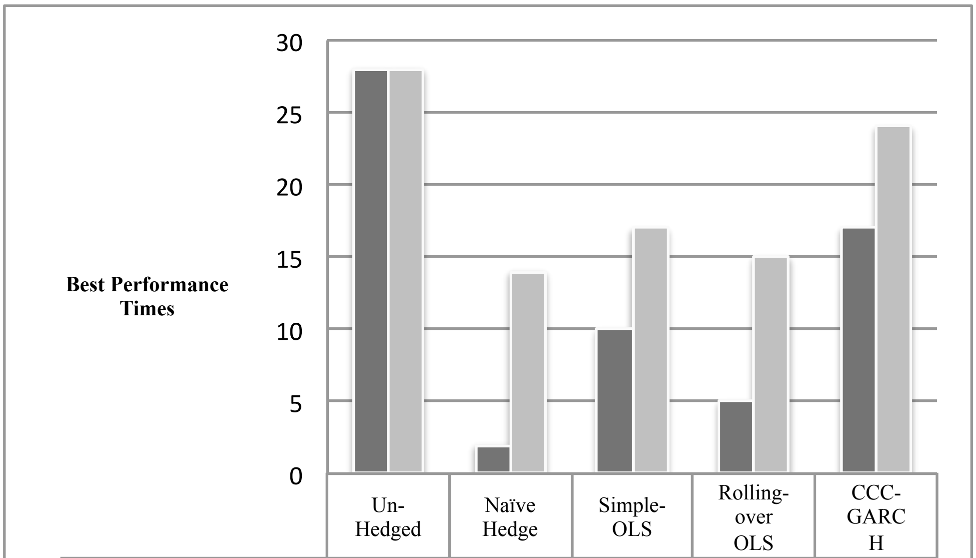
1). All hedging strategies decrease returns of cotton spot. Return of un-hedged portfolio is 5.58 in average for the whole evaluation periods, and returns of hedged portfolios are mostly around 2.0 in average except “Naïve Hedge”;

2). Strategies that with predicted variance in advance to decide whether to hedge is better than that without predicted variance. Except “Naïve Hedge”, the returns of the former one are around 2.4-2.5and that of the later one are around1.7-1.8;

3). For both strategies (with or without predicted variances filter), CCC-GARCH performs the best, Simple-OLS plays the second, Rolling-over OLS is the third and Naïve Hedge is the last;

4). The same as the results of variance performance, Rolling-over OLS is worse than Simple-OLS no matter in which strategies (with or without predicted variances filter).

In addition to Table 7, Figure 10 is the “best performance” times of different hedging strategies with returns. Obviously seeing from the figure, Un-Hedged strategy is always the best choice if only considering expected returns. At the same time, the price of risks is high. So if including portfolio variance as consideration, then CCC-GARCH always has the highest “best performance” times for both strategies with or without predicted variance filter. Simple-OLS and Rolling-over-OLS are the second and third performers respectively, and Naïve Hedge is the last.



	Un-Hedged	Naïve Hedge	Simple-OLS	Rolling-over OLS	CCC-GARCH
Without Predicted Variance	28	2	10	5	17
With Predicted Variance	28	14	17	15	24

Figure 10: Returns of alternatives hedging strategies: Best performance times

Thus in conclusion with all the information, except "Un-hedged" strategy, "CCC-GARCH with predicted variance filter" is the best choice for hedging risks of the cotton spot price volatility if only considering "expected returns" objective.

6.3 Sharpe-Ratio Performances of Hedging Strategies

In section 6.1 and 6.2, CCC-GARCH with and without predicted variance filter are concluded as the best choices for hedging cotton prices risks respectively under the objective conditions of "minimum variance" and "expected returns". Conclusions above are inconsistent to each other. For making a more reasoned conclusion, objectives of minimum variance and expected returns should be considered in the same time.

Sharpe-Ratio is one of the most popular ways for measuring the relation between portfolio's variance and expected return. It measures the excess return per unit of risk in an investment asset. It is given as:

$$Sh = \frac{E(r_t)}{\sqrt{Var(r_t)}} \qquad (6.3.1)$$

Table 8 is the results of Sharpe-Ratio for all hedging strategies.

Table 8 Sharpe ratios of alternatives hedging strategies

Sharpe Ratios of alternatives Hedging Strategies				
Condition	**Naïve Hedge**	**Simple-OLS**	**Rolling-over OLS**	**CCC-GARCH**
Without Predicted Variance	0.055129163	0.218953288	0.2139606	***0.23121048***
With Predicted Variance	0.15438896	0.279855285	0.276450434	***0.28773211***

Sharpe-Ratios of CCC-GARCH are 0.23 and 0.29 in strategies that without and with predicted variance filter respectively. It performs the best of all. The second performer is Simple-OLS, which has ratios of 0.22 and 0.28 respectively. Rolling-over OLS is the third but very close to Simple-OLS. Naïve Hedge is the last. Thus, in conclusion, according to Sharpe-Ratios "CCC-GARCH with predicted variance filter" is the best strategy for hedging the cotton spot price volatility with considering both expected return and variance of portfolio.

6.4 Quadratic Utility Values of different Hedging Strategies with alternative Risk Aversion Levels

In practice when choosing an optimal hedging strategy, individual's risk aversion level has to be included into consideration. Table 9 exhibits the quadratic utility values of alternative hedging strategies under different risk aversion levels for the whole evaluation periods.

Table 9 Quadratic utility values of alternatives hedging strategies

Quadratic Utility Values of alternatives Hedging Strategies under different Risk Aversion Levels										
Risk Aversion	**Without Predict Variance**					**With Predict Variance**				
	Un-hedged	**Full Hedged**	**Simple-OLS Hedged**	**Rolling-over-Hedged**	**CCC-GARCH Hedged**	**Un-hedged**	**Full Hedged**	**Simple-OLS Hedged**	**Rolling-over-Hedged**	**CCC-GARCH Hedged**
-3	0.07012	0.01656	0.02746	0.02711	0.02848	0.07012	0.02702	0.03639	0.03612	0.03707
-2	0.06536	0.01266	0.02420	0.02384	0.02521	0.06536	0.02276	0.03249	0.03222	0.03318
-1	0.06060	0.00876	0.02094	0.02057	0.02195	0.06060	0.01850	0.02860	0.02832	0.02929
0	0.05584	0.00487	0.01768	0.01730	0.01868	0.05584	0.01425	0.02470	0.02442	0.02539
1	***0.05108***	0.00097	0.01442	0.01403	0.01542	0.05108	0.00999	0.02081	0.02052	0.02150
2	***0.04632***	-0.00293	0.01116	0.01076	0.01215	0.04632	0.00573	0.01691	0.01662	0.01760
3	***0.04156***	-0.00682	0.00790	0.00749	0.00889	0.04156	0.00147	0.01302	0.01272	0.01371
24	***-0.05841***	-0.08866	-0.06056	-0.06116	-0.05967	-0.05841	-0.08793	-0.06879	-0.06921	-0.06806
25	-0.06317	-0.09256	-0.06382	-0.06443	***-0.06294***	-0.06317	-0.09219	-0.07268	-0.07311	-0.07196
37	-0.12029	-0.13933	-0.10294	-0.10366	***-0.10212***	-0.12029	-0.14754	-0.11164	-0.11992	-0.13629
38	-0.12505	-0.14322	-0.10620	-0.10693	***-0.10538***	-0.12505	-0.14754	-0.12332	-0.12383	***-0.12258***
39	-0.12981	-0.14712	-0.10946	-0.11020	***-0.10865***	-0.12981	-0.15180	-0.12722	-0.12383	***-0.12647***
40	-0.13457	-0.15102	-0.11272	-0.11347	***-0.11191***	-0.13457	-0.15606	-0.13112	-0.13163	***-0.13036***

As we can see from Table 9, if considering both strategies with and without predicted variance filter, then the optimal strategy under different risk aversion level is:

1). For individual who is risk lover ($RiskAversion < 0$), such a person will never choose to hedge risk as he or she likes risk. Therefore he or she will never engage in any risk reducing schemes. "Un-hedged" strategy is the best choice.

2). For individual who is risk neutral ($RiskAversion = 0$), he or she is indifferent between the bet and a certain return. Thus such a person can either choose "Un-hedged" strategy or "CCC-GARCH with predicted variance filter" to hedge the risks of cotton spot volatility. Normally, such a person will not employ any hedging strategy;

3). For individual who is risk averter ($RiskAversion > 0$), the utility value of alternative hedging strategies varies with different risk aversion levels. Figure 11 is the patterns of three strategies' utility values: "Un-Hedged", "CCC-GARCH without predicted variance filter" and "CCC-GARCH with predicted variance filter".

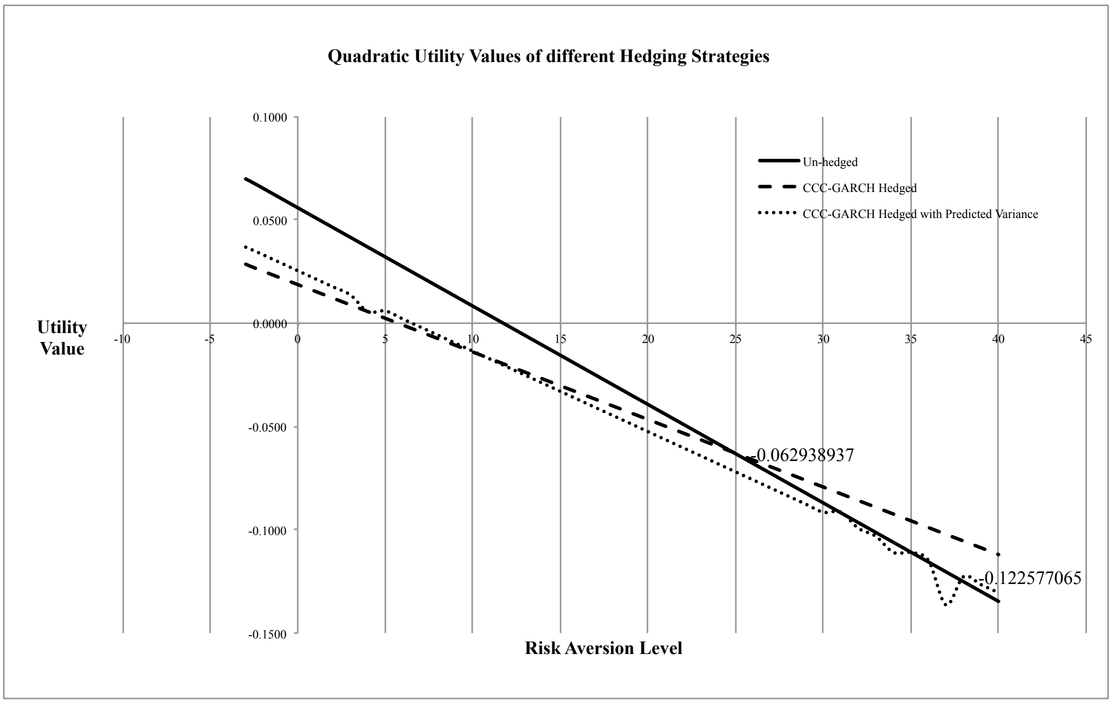


Figure 11: Quadratic utility values of alternatives hedging strategies

As can be seen from Table 9 and Figure 11, in general, "Hedged" strategy outperforms "Un-hedged" strategy only when risk aversion is high enough. In addition, strategy that with predicted variance filter only outperforms strategy that without predicted variance filter when risks aversion is lower than 11. More specifically, a) for risk aversion is lower than 11 ($RiskAveresion < 11$), "Un-hedged" portfolio has the highest utility value, "CCC-GARCH with predicted variance filter" is the second and "CCC-GARCH without predicted variance filter" is the last; b) for risk aversion is between 11 to 25 ($11 < RiskAveresion < 25$), "Un-hedged" portfolio is the best, "CCC-GARCH without predicted variance filter" is the second and "CCC-GARCH with predicted variance filter" is the last; c) for risk aversion is equal to or higher than 25 ($RiskAveresion \geq 25$), "CCC-GARCH without predicted variance filter" is better than "Un-hedged" strategy; d) for risk aversion is larger than 37 ($RiskAveresion > 37$), "CCC-GARCH with predicted variance filter" is better than "Un-hedged" but still worse than "CCC-GARCH without predicted variance filter".

All in conclusion, individual who is risk averter will choose "CCC-GARCH without predicted variance filter" to hedge risks of the cotton price volatility only when his or her risk aversion is high enough (in this case is $RiskAveresion \geq 25$). Except this condition, "Un-hedged" strategy is the best choice.

7 Summary and Conclusion

This paper investigated the behaviors of cotton future hedging in U.S. market with different hedging strategies. Empirical results clearly answer the research questions in section 1.

For the first question "Can an optimal hedge ratio help to improve the performance of cotton future hedging in U.S. market?", all hedging strategies effectively reduce risks of the cotton spot price volatility. The variances of hedged portfolio are smaller that the variances of un-hedged one. According to the variance performances results, the average variance of un-hedged portfolio is 95.20, and most of the average variances of hedged portfolios are around 65. In general, all of the tested hedging strategies except "Naïve Hedge" can reduce the variance of un-hedged portfolio up to around 31%, and the "Naïve Hedge" strategy can reduce 18% of variance.

Although the variance-reduction effect is obviously, but in the other hand these hedging strategies impact the returns of cotton spot asset in different levels. More specifically, under different objective conditions, the examined hedging strategies have different behaviors. With the objective condition of "minimum variance", "CCC-GARCH without predicted variance filter" is the best choice for hedging the risks of cotton spot prices volatility; but if considering "expected returns", "CCC-GARCH with predicted variance filter" then is the best choice for hedging risks of the cotton spot price volatility. This remarkable results just answer the second research question in section 1 that "Can an accurate period-ahead variance forecasting in the spots market help traders of cotton futures to maximize their benefits by adjusting hedging strategies?" As that have been discussed, strategy that with predicted variance in advance to decide whether to hedge does not always play the best. Its performance depends on particular circumstance. Additionally, since these conclusions are inconsistent and only include one objective condition in one time, Sharpe-Ratio is further implemented as the measure of strategies' performance. Results of Sharpe-Ratio exhibit that "CCC-GARCH with predicted variance filter" is the best strategy for hedging the cotton spot price volatility with considering both expected return and variance of portfolio in the same time.

However, for choosing an optimal hedging strategy in practice, risk aversion level has to be included into consideration. In general, "Hedged" strategy outperforms "Un-hedged" strategy only when risk aversion is high enough. In addition, strategy that with predicted variance filter only outperforms strategy that without predicted variance filter when risks aversion is lower than 11 ($RiskAveresion < 11$). Individual who is risk averter will choose "CCC-GARCH without predicted variance filter" to hedge risks of the cotton price volatility only when his or her risk aversion is high enough (in this case is $RiskAveresion \geq 25$). Except this risk aversion level, "Un-hedged" strategy is the best choice.

Although most of the empirical results in this paper are consistent to theoretical expectation, but some of them are not. The first inconsistency is that CCC-GARCH does not overall outperform OLS family and additionally Rolling-over-OLS does not play better than simple-OLS. This can be probably caused by the short periods of evaluation. In the future study, the extended evaluation periods could be carried to examine these three models. The second inconsistency is strategy that combined with predicted variance filter does not perform as good as the expectation. This method maybe too simple to accomplish the best effectiveness that predicted variance can provide. As referencing from some previous studies (e.g. Wu, Liu, & Yang, 2009), it may be better if the hedged ratio (h_t) that is based on in-the-sample estimations can be replaced with the ratio (h_{t+1}) that is calculated with out-of-sample estimations. Finally, another improvement that can be made is about DCC-GARCH. In this paper, results of DCC-GARCH cannot be properly ran out because of its complexity, and further exploration is beyond the scope of this study but represents also another future extension of this study.

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9 Appendix

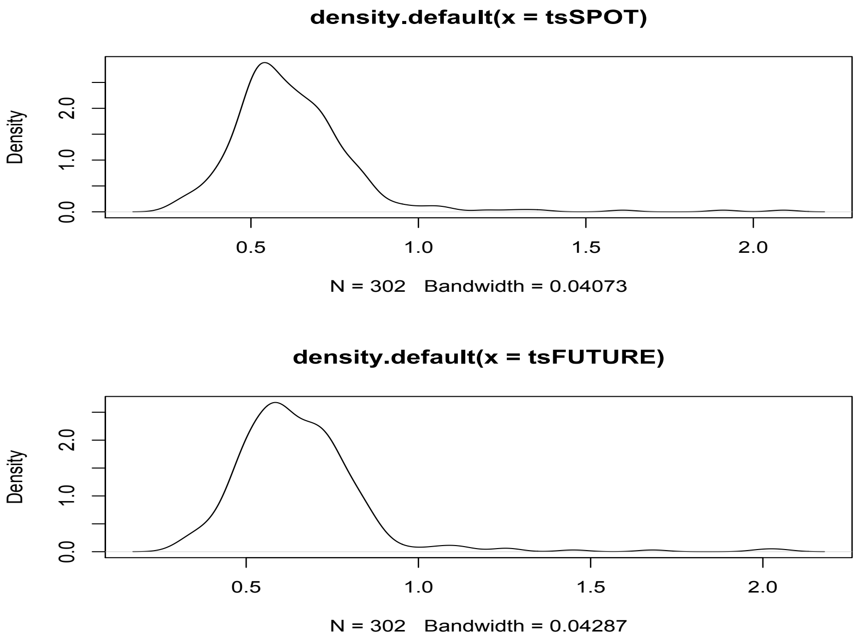

Figure 4: Density of cotton spot and futures in levels

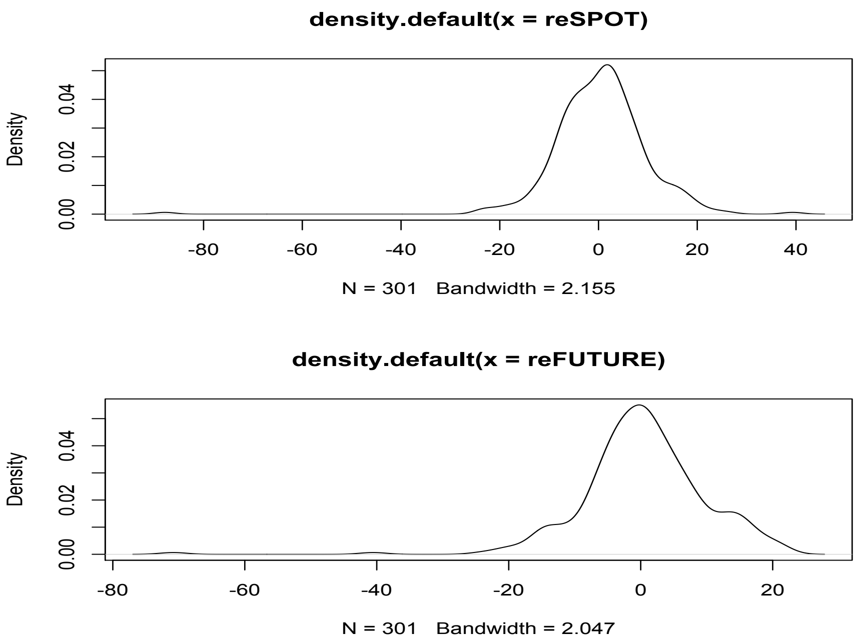

Figure 5: Density of cotton spot and futures in returns

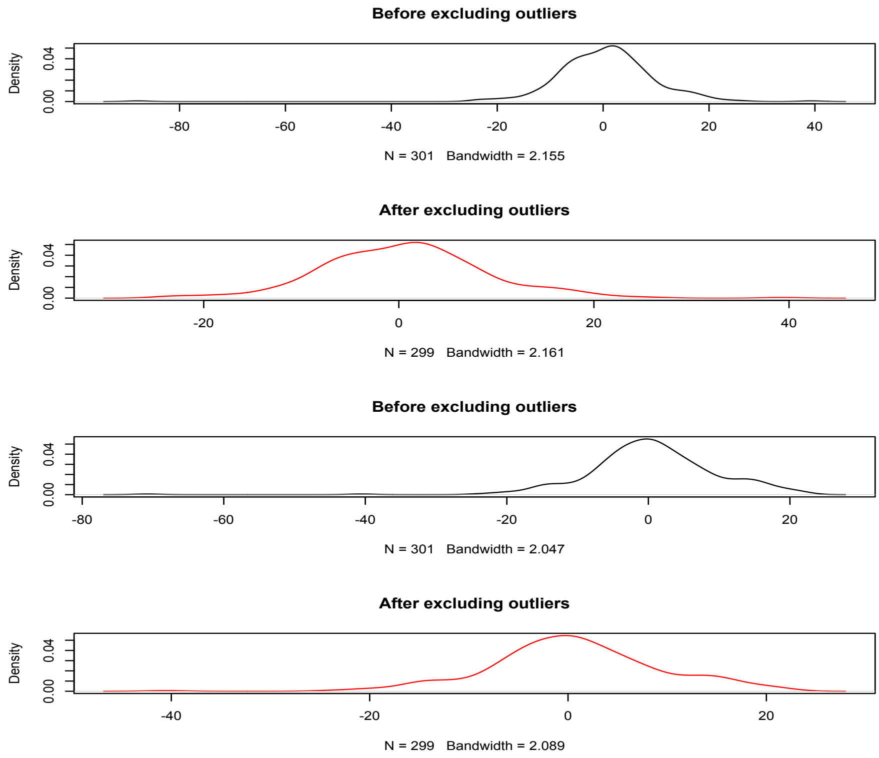

Figure 6: Densities of cotton spot and futures before and after excluding outliers

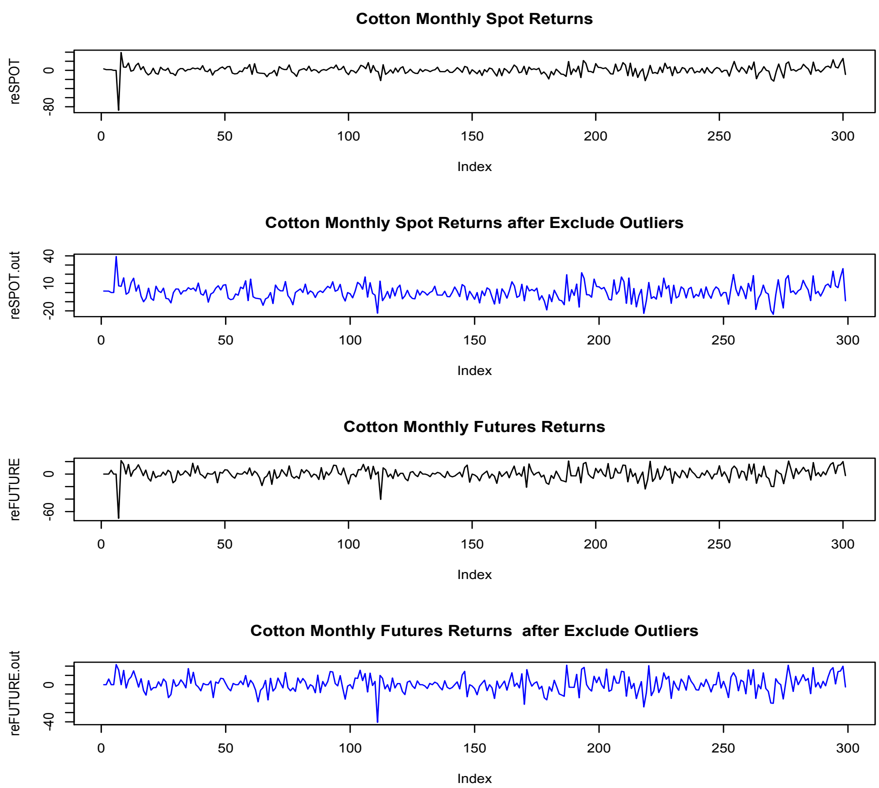

Figure 7: Patterns of cotton spot and futures before and after excluding outliers

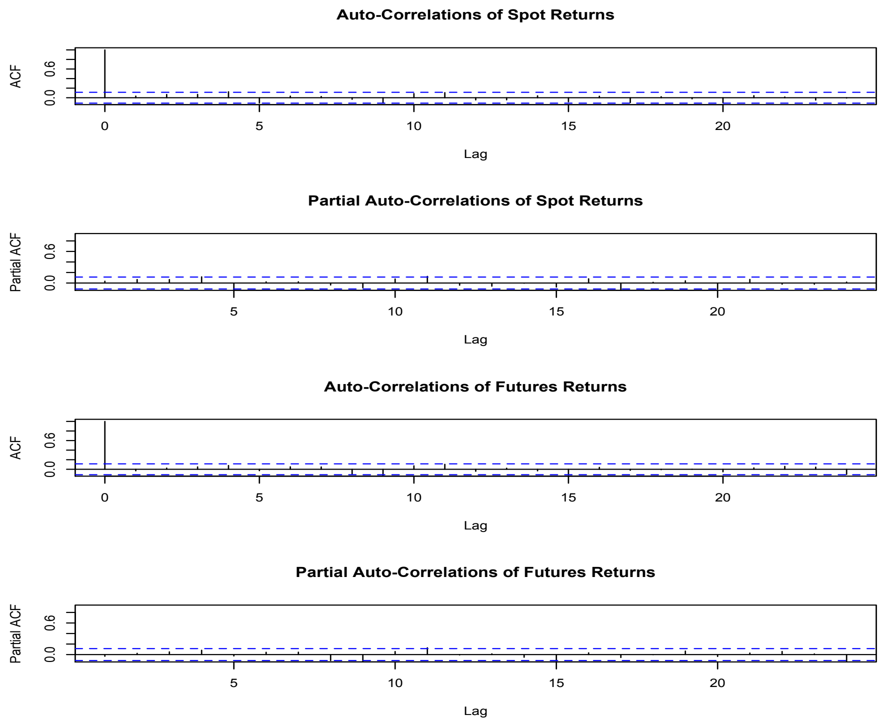

Figure 8: ACF & PACF of mean adjusting cotton spot and futures