# Agricultural Commodities:
# Risk Management for Exporting Countries

by

KOMKRIT OVARARIN

Imperial College Business School
Imperial College London

August 2012

Submitted to Imperial College London
In partial fulfilment of the requirement for the degree of
Doctor of Philosophy

# Acknowledgements

First and foremost I am deeply thankful and indebted to my supervisor Professor Nigel Meade for his intellectual inspiration, intelligence, encouragement and especially for his patience and whole-hearted support though the time of research and writing. This thesis would not have been of the same calibre without his support.

I would like to take this opportunity to sincerely acknowledge the Suratthani Rajabhat University (SRU) in the name of Thai's Government for providing me with the scholarship that allowed me to study and contribute to this research. A special thank you goes to my colleagues at SRU, Prayote, Paungpen. Taungkran, Thanawit, and Chompunut and also close friends in Thailand, Thanawut, Danai, Pintaya and Premjit for their great friendship and support.

I would also like to express gratitude towards my peers at Imperial College, who provided a great research environment and a friendly discussion forum. Filip, LingLing, Pascal, Lei, Nick, Lorenzo, Adriana, Panita and Boonyavee have helped in many meaningful ways during this time, as have all the Thai PhD students at Imperial College. Worrawat, Piyamas and Yada have been crucial contributors to my success. These notable individuals have made my time at Imperial College a truly unforgettable experience.

Finally, I would like to express infinite gratitude to my loving family; to my parents and my uncle for providing me with crucial support throughout my life and to my sisters, my brother-in-laws, my nephews and my niece that have always made me laugh via fun Skype exchanges. This thesis is dedicated to them.

Komkrit Ovararin

# Abstract

We consider three aspects of agricultural risk management: volatility modelling of commodity returns for several agricultural commodities, convenience yield modelling for various commodities and weather risk in Thailand, a supplier of rubber, sugar and rice.

To model the volatility of commodity returns, we extend the GJR-Generalized Autoregressive Conditional Heteroskedasticity (GJR-GARCH). The inclusion of seasonal patterns, composed of a day-of-the-week effect (representing investor behaviour) and a yearly effect (representing harvest yields) are important in providing more accurate models of volatility. To capture fat tails, Standardised-t and the generalised error distribution (GED) are employed in estimations and compared with Gaussian error distribution. The Value-at-Risk (VaR) of the optimal volatility model's forecasting performances are used to determine the accuracy of these models.

The second study examines convenience yield modelling and heteroskedasticity. The analysis of seven agriculture net convenience yields clearly shows that the benefit of net convenience yield exists only in the short term, otherwise it converges to zero. Both the current tests and a new proposed test confirm the existence of heteroskedasticity. An autoregressive model is used to model convenience yield: GARCH (1,1) and Standardised-t are more accurate than the alternatives considered. Finally, the net convenience yield is investigated in the context of the international market. We found that the depreciation of exchange rates of the leading exporting countries eliminates the benefit of holding the agricultural product.

In the final study, we devised a weather insurance model, a hybrid error distribution that captures two important daily rainfall characteristics, to assess the weather risk to the Thai agricultural products. Our probability distribution combines a seasonal-Weibull distribution, which captures moderate rainfall, with an Extreme Value distribution, which captures extreme to heavy rainfall. Monte Carlo methods are used to simulate the daily data in order to compare our model performances with the actual data and estimate the rainfall insurance premium.

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# Chapter 1

# Introduction

This thesis focuses on several significant risks for agricultural exporters. During the initial stages of this thesis, we identify the major risks for large agribusinesses in Thailand through interviews and through the examination of official agricultural documents. Agribusiness owners and farmers fear price risk and production risk, and these two risks cannot be eliminated by using only local financial markets due to lack of liquidity. An other important risk factor for the Thai agricultural community is exchange rate risk because many products are exported. Exchange rate risk management in Thailand is at a mature stage: various financial services and instruments are generally offered by a commercial banks and import-export banks within the country.

Weather is also a crucial risk for Thai farmers because unexpected inclement weather may cause substantial losses. Weather insurance receives less attention in Thailand because of distrust of the insurance market. However, the government has campaigned during the last decade to reinforce consumer confidence in insurance and increased the insurance fund with a view to reinvesting the money in the other financial markets in order to increase liquidity for Thailand's financial market. At present, the Agriculture and Cooperative Agriculture Bank of Thailand sell weather insurance with a loan. This means that the bank will be compensated by an insurer if the party taking out the loan cannot pay the bank as a result of weather issues. Weather insurance in the form of the weather derivative market is popular in the USA, especially at the Chicago Mercantile Exchange (CME).

The background of the Thai economy will be discussed, especially in the agriculture section

of Chapter 2, which explains how agriculture is important to the Thai economy and also discusses the current state of local and international agricultural markets for rubber, rice and sugar. Chapter 3 examines both general and agricultural risk management through literature reviews. Due to the dependence between the Thai economy and seasonal agriculture, the theory of seasonal effects is also explained.

Chapter 4 is focused on risk modelling for agricultural prices. We consider rubber, white sugar and rough rice. All futures prices are collected from the international leading active agriculture futures markets. The first step is the modelling of volatility for all three agricultural time series. The volatility model is adapted to include seasonality components, as these effects were detected while composing stylised statistics for these commodity returns.

All three commodity returns exhibit high kurtosis implying fat-tailed distribution of returns. Standardized-t and the generalised error distribution (GED) are considered as error distributions to capture fat tails. The seasonal volatility model is evaluated in a Value at Risk experiment. The accuracy of forecasting is determined by two backtesting methods: a binomial test and an independence test (Engle and Manganelli, 2004).

In Chapter 5, convenience yield, a distinctive element in the commodity future pricing formula introduced by Working (1930) and Kaldor (1939), is studied. We examine seven agricultural products: rubber, rough rice, white sugar, raw sugar, coffee, corn and cotton. Stylized facts are derived for the different maturities of the futures contracts investigated. Net convenience yield is estimated by a backwardation approach, and then the term structures of net convenience yields are plotted. The second objective of this chapter is to model the net convenience yield. The convenience yield modelling used in this thesis was initially based on the research paper of Lui and Tang (2011). They demonstate the convenience yield volatility relationship that we can be rearranged to an autoregressive model (AR(1) model). The heteroskedasticity tests employed in this thesis are the Breusch-Pagan test, the Glejser test, the Harvey test and the ARCH test. In addition, we propose a new heteroskedasticity test that contains residual lag and variable lag. Both the newly proposed heteroskedasticity test and the other tests confirm the existence of heteroskedasticity in our samples. We introduced a

two- time varying volatility model, Generalized Autoregressive Conditional Heteroskedasticity (GARCH), and an Integrated Generalized Autoregressive Conditional Heteroskedasticity (IGARCH); moreover, an assumption of fat-tail distributions was also made because we found a high kurtosis in all samples. A further study of convenience yield in international commerce was conducted based on the assumption that some agricultural products are not grown in the future trade market location. Hence, the benefit of holding the physical product probably depends upon the relevant exchange rate. We examine the hypothesis that the depreciation of exporting country's currency to the futures market destroys the benefit of holding the commodity. In regards to Thai exports, only rubber, white sugar and raw sugar are tested in this thesis.

In Chapter 6, the weather risk for farmers in tropical areas is assessed. Rainfall levels directly affect farm production. This study aims to propose a rainfall model for four Thai weather stations. The four stations were selected due to their location in growing areas for rubber, sugar cane and rice. The rainfall model employed in this thesis is based on a two-step approach. Firstly, the seasonal unconditional probability of rain-days is estimated using a trigonometric function. Secondly, a hybrid distribution is created to model the daily rainfall level. This probability distribution consists of a seasonal-Weibull distribution, which captures moderate rainfall, and an Extreme Value distribution, which captures extreme-to- heavy rainfall. Monte Carlo methods are used to simulate the daily data in order to compare our model performance with the actual data and to study the rainfall index-insurance premium. Monthly and 30-dayss High rainfall (HR) and Low rainfall (LR) insurance premiums are illustrated with constant and seasonal strike prices.

Finally, Chapter 7 reviews the results of the three main research chapters. This thesis aims to exhibit the benefits of the results, which may help to improve the agricultural market, especially in Thailand, as well as offer recommendations and suggestions for future research.

# Chapter 2

# Agriculture Commodity Market Background

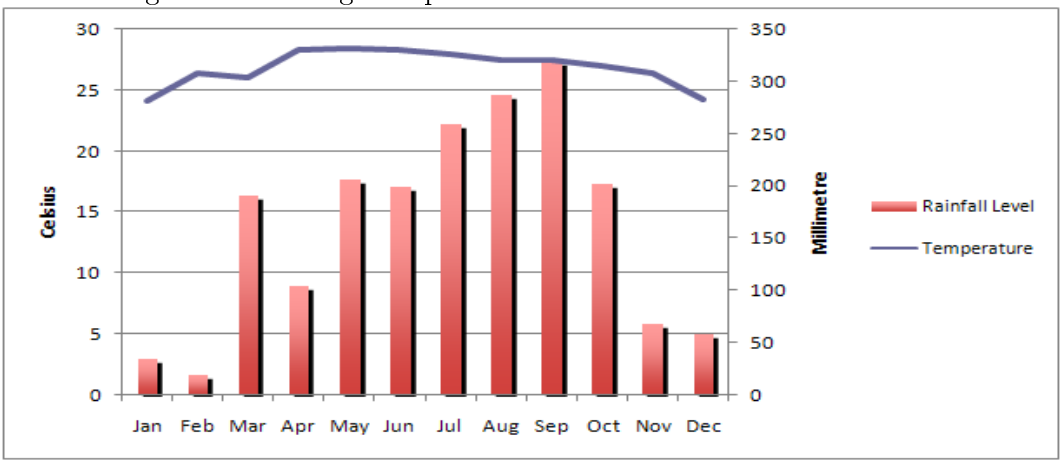
## 2.1 Thailand Background

Thailand was established as an independent nation in the mid-14th century. Located in Southeast Asia, its estimated population was 64.8 million people at end of 2011. Situated between 5° 37' and 20° 28' North latitude and 97° 51' and 105° 38' East longitude. Thailand has three typical seasons: rain, cool and hot. It is a tropical monsoon climate. The weather is normally hot, with high humidity: the average temperature of Thailand is 26.82 Celsius, and the cumulative of average rainfall of Thailand is approximately 1,948 millimetres in 2011 as shown in Figure 2.1.

The gross domestic product (GDP) was 10,539 billion baht in 2011 (approximately £ 214.17 billion). The World Bank categorizes Thailand as a middle-income country. The value of Thailand exports was 6,872.45 billion baht, which accounted for more than two-thirds of the gross domestic product (GDP). The central exporting products consist of machinery and electronic components, jewellery and commodity products.

After the Asian crisis in 1997, the GDP growth rate had been around 4 % since 2000 to 2004. However, Thailand's economy has not grown smoothly during the last few years, especially in the period from 2007 to the present. The unstable political situation since 2007 has resulted in a low growth rate of about 3 %. Political uncertainty has damaged Thailand's

Figure 2.1: Average temperature and rainfall of Thailand in 2011




Source: Rainfall and Severe Flooding Over Thailand in 2011 by Climatological Center, Thailand Meteorological Department

economic growth.

Thailand's low economic growth could be a result of demographic changes, especially in the career choices of working-age persons. Thailand's national statistics department reports the number of employed persons who are 15 years old and older by occupation. The occupations listed consist of 10 major career categories: legislators, senior officials and managers; other professionals; technicians and associate professionals; clerks, service workers and shop and market sales workers; skilled agriculture and fishery workers; craft and related trades workers; plant and machine operators and assemblers; elementary occupations; and workers not classifiable by occupation.

The largest group of employed persons is the skilled agriculture and fishery workers, at approximately 35 per cent. However, the contribution of this sector to the Thai gross domestic production (GDP) is about 10 per cent. This fact reveals that even though the majority of the Thai workforce are skilled agriculture and fishery workers, they are not able to generate a high value in production.

There are two potential reasons to explain why the production value is low. Firstly, the price effect is a considerable factor. For example, farmers may grow crops that do not have a good sale value or they may farm crops that are not in demand. Secondly, the production risk

is also a possible factor of their relatively lower value in production. For instance, a production yield may be low according to inadequacy of technological support, pest protection control or less nutritious resources for the crops.

The major crops grown in Thailand over the last decade are rice, natural rubber, cassava and sugar (Food and Agriculture Organization of the United Nations : FAO, 2011). Thailand is the world's largest producer of many agricultural products, including rice, natural rubber, corn, sugar cane, coconut and soybeans. Its predominance as an agricultural exporter is partially due to its environmental factors: its temperature, humidity level and fertile soil.

Thailand is a world leader in natural rubber production and export. In 2011, Thailand's natural rubber production was 3,569 thousand tons. The export value was 383,318.60 million baht, which is equivalent to 3.64 % of the GDP (Office of Agricultural Economics, Thailand). The main destination of exported rubber is provided on the website of the Rubber Research Institute of Thailand. China is the main importer of Thai rubber, 35.71%, followed by Malaysia and Japan, 15.10% and 13.35% respectively. However, between 1993-2002, Japan was the leading importer of rubber from Thailand. The significant increase in demand from China started in early 2000 and has continued to the present.

Table 2.1: Rubber exporting volume by destinations (Tons)

| Country | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 |
|---|---|---|---|---|---|---|
| **Japan** | 492,740 | 405,599 | 394,742 | 256,984 | 346,302 | 333,669 |
| **China** | 747,168 | 827,369 | 824,833 | 1,160,339 | 1,128,553 | 1,274,188 |
| **USA** | 210,784 | 213,080 | 219,986 | 156,069 | 177,859 | 205,410 |
| **Malaysia** | 442,664 | 413,049 | 398,043 | 480,313 | 443,000 | 344,589 |
| **South Korea** | 173,477 | 151,824 | 154,340 | 133,079 | 171,530 | 186,634 |
| **Europe** | 261,882 | 262,182 | 249,509 | 245,589 | 268,693 | 223,938 |
| **Other** | 442,958 | 430,659 | 433,830 | 293,820 | 330,510 | 383,953 |
| **Total** | 2,771,673 | 2,703,762 | 2,675,283 | 2,726,193 | 2,866,447 | 2,952,381 |

Source: Thailand Rubber Research Institute

Rice has a distinguishing feature depending on the production location, for example, Japanese rice is dissimilar to Indian basmati rice; therefore, it is complicated to identify the world's leading exporter of rice. In general, China and India are world largest rice producers, but their rice is mainly sold domestically. Thailand is also amongst the top world rice pro-

ducers: in 2009, Thailand was ranked seventh worldwide producing about 32,116,100 million tons of rice (FAO).

In 2011, Thailand exported approximately 10,706 thousand tons of rice (Office of Agricultural Economics, Thailand), which was equivalent to approximately 196,117 million baht. This is approximately 1.86% of GDP. Thai rice is mainly exported to Africa (45.17%) followed by the Asia, the Middle East, Europe, America and Oceania. The top ten importers of Thai rice are Nigeria, Indonesia, Bangladesh, Republics of Iraq, Iran, Ivory Coast, South Africa, USA, Malaysia, Ghana and Japan.

Table 2.2: Thai rice exporting volume to region (Tons)

| **Region** | **2006** | **2007** | **2008** | **2009** | **2010** | **2011** |
|---|---|---|---|---|---|---|
| **Asia** | 2,069,285 | 2,890,639 | 2,473,681 | 1,763,635 | 2,198,888 | 3,407,551 |
| **Middle East** | 1,577,274 | 1,465,148 | 1,354,416 | 898,508 | 1,251,044 | 1,374,965 |
| **Europe** | 404,592 | 646,961 | 838,063 | 592,332 | 479,517 | 488,650 |
| **Africa** | 2,736,271 | 3,922,286 | 4,600,185 | 4,596,551 | 4,431,798 | 4,687,962 |
| **America** | 483,040 | 477,008 | 546,677 | 537,885 | 488,387 | 518,315 |
| **Oceania** | 150,193 | 155,339 | 198,013 | 203,920 | 197,752 | 188,678 |
| **Total** | 7,420,656 | 9,557,382 | 10,011,035 | 8,592,830 | 9,047,386 | 10,666,121 |

Source: Thailand Rice Exporters Association

Table 2.3: Top ten destinations of Thai rice in 2011 (Tons)

| **Rank** | Countries | Volume | **Rank** | Countries | Volume |
|---|---|---|---|---|---|
| **1** | Nigeria | 1,549,964 | **6** | South Africa | 561,200 |
| **2** | Indonesia | 914,918 | **7** | USA | 397,499 |
| **3** | Bangladesh | 736,782 | **8** | Malaysia | 330,832 |
| **4** | Republic of Iraq | 627,300 | **9** | Ghana | 311,429 |
| **5** | Ivory Coast | 568,046 | **10** | Japan | 307,986 |

Source: Thailand Rice Exporters Association

Sugar cane production in Thailand was ranked fourth of world producers in 2009 (FAO). White and raw sugar industry was the second most lucrative exported product, valued at approximately 1.16 % of GDP in 2011. Thailand exports 2,375 and 4,116 thousand tons (45,823 and 62,876 million baht) of white and raw sugar respectively (Office of Agricultural Economics, Thailand). A significant increase in demand is not only associated with consumption, but also with industry usage, such as ethanol. Thai sugar mainly is exported to Asian countries, which

account for 82% of the total sugar exporting volume, as show in Table 2.4. In addition, the top ten importers of Thai sugar, which are represented in Table 2.5, are Asian countries.

Data was collected from the office of The Cane and Sugar Board of Thailand. Even though the main destinations of Thai sugar are in Asia, the office of The Cane and Sugar Board of Thailand use the raw sugar futures price of the New York Board of Trade and the white sugar futures price of the London International Futures and Options Exchange as the reference prices.

Three types of agriculture have been discussed, which are the main exporting products of Thai agribusinesses. All agricultural prices use the international future exchange market as the standard reference price. However, cassava is a unique product which has no international trading market as a reference price. Table 2.6 represents the export quantity and value of the three main exported commodities in the cash market.

Even though a significant income is generated from the agricultural sector, the majority of the Thai population residing in rural areas and employed in the production of agricultural products live in poverty. Therefore, most of the elected government projects focus on the agricultural sector, which is a common political strategy in a developing country. The government needs support from the majority population.

In addition, when the benefits of commodity price control and risk management in the future exchange market were made apparent, Thailand established the agriculture future exchange market (1999). There are three main underlying agricultural products in the future exchange market: rubber, rice and cassava. However, after more than 10 years of an introduction period, Agriculture Future Exchange Thailand (AFET) still encounters many issues, such as the lack of traders' interest and participants' incorporation, which has led to its late development.

Table 2.4: Sugar exporting volume by destination (Tons)

| Region | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 |
|---|---|---|---|---|---|---|
| **Asia** | 2,094,966 | 3,319,037 | 4,321,161 | 4,099,847 | 3,687,677 | 5,334,918 |
| **Middle East** | 63,896 | 999,813 | 447,025 | 536,707 | 489,897 | 646,172 |
| **Europe** | 1,808 | 33,373 | 19,721 | 133,295 | 476 | 36,057 |
| **Africa** | 4,603 | 116,090 | 68,399 | 245,462 | 193,213 | 450,451 |
| **America** | 25,255 | 21,315 | 12,262 | 19,860 | 24,047 | 26,689 |
| **Oceania** | 6,481 | 7,368 | 13,797 | 63,755 | 83,620 | 186,784 |
| **Total Volume (Tons)** | 2,197,009 | 4,496,996 | 4,882,365 | 5,098,927 | 4,478,930 | 6,681,070 |
| **Total Value (Thai Baht)** | 27,388,404,287 | 44,527,272,345 | 47,534,165,416 | 62,991,168,206 | 70,844,879,563 | 122,510,148,241 |

Source: Office of The Cane and Sugar Board of Thailand

Table 2.5: Top ten destinations of Thai sugar exports in 2011

| Rank | Countries | Volume | Rank | Countries | Volume |
|---|---|---|---|---|---|
| **1** | Indonesia | 1,316,050 | **6** | Malaysia | 343,703 |
| **2** | Japan | 1,079,771 | **7** | Vietnam | 289,757 |
| **3** | South Korea | 508,164 | **8** | Egypt | 277,572 |
| **4** | Republic of Iraq | 397,242 | **9** | Taiwan | 222,906 |
| **5** | Cambodia | 389,209 | **10** | Singapore | 183,631 |

Source: Office of The Cane and Sugar Board of Thailand

## 2.2 Thailand Agricultural Futures Market

The Ministry of Commerce of Thailand established the Agricultural Future Exchange of Thailand (AFET), an independent private organization, in 1999. However, there was a long period of development and the first trading was conducted in 2004. The first futures contract was Natural Rubber Ribbed Smoked Sheet No.3 (RSS3), traded on 28 May 2004. At present, the underlying commodities currently trading are Natural Rubber Ribbed Smoked Sheet No.3, Tapioca Chips, White Rice 5% Both Options, and Thai Hom Mali Rice 100% Grade B Both Options.

The main objectives of AFET are to develop and provide effective hedging tools for farm cooperatives, producers, traders and manufacturers who seek to reduce their risk from price uncertainty in agricultural products. AFET attempts to provide reliable prices as an international benchmark for key agricultural commodities prices. However, we found that some prices of futures contracts traded in the AFET are not the best indicator of agricultural prices in the cash market nor do they function as a benchmark for the international price.

From the historical market trading data, the highest volume trading is in Rubber futures contracts followed by White Rice 5% futures contracts. The Rubber futures price is an important price which can be used as a national and global benchmark because of the massive volume of trading and the non-intervention of the government. On the other hand, the second largest trading volume is White Rice 5% which is not a good benchmark for international prices because of price disturbances (government interventions).

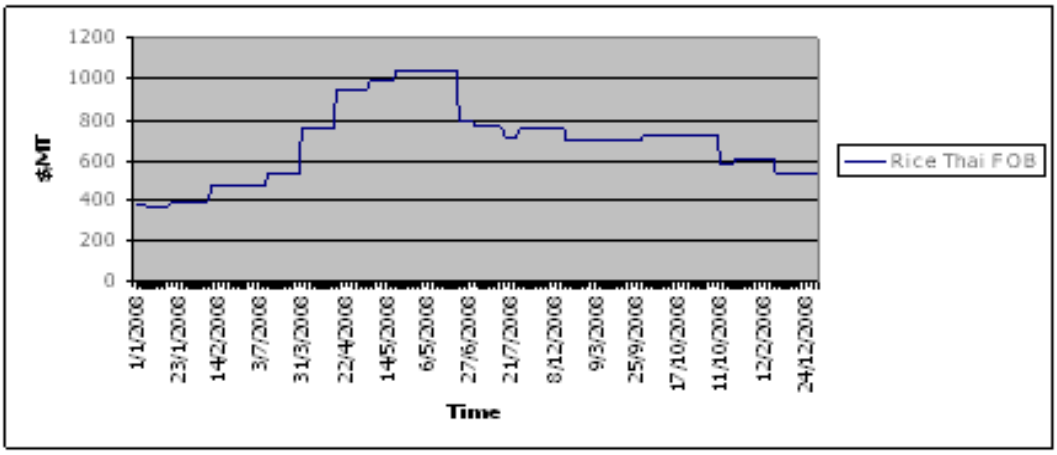
Thailand and Vietnam are the leading rice exporters. Normally, exporters apply the trad-

Table 2.6: Export Quantity and Value of rubber, rice and sugar from Thailand between 2005 and 2011

| **Rubber** | **2005** | **2006** | **2007** | **2008** | **2009** | **2010** | **2011** |
|---|---|---|---|---|---|---|---|
| **Quantity** | 920,384,879 | 940,263,729 | 866,723,429 | 766,461,502 | 686,359,171 | 691,203,745 | 753,599,850 |
| **Value** | 52,160,281,639 | 71,852,982,599 | 63,288,394,810 | 68,971,946,473 | 42,895,554,424 | 72,828,287,394 | 115,372,224,851 |
| **Rice** | | | | | | | |
| **Quantity** | 7,495,903,816 | 7,494,140,078 | 9,192,517,546 | 10,216,127,754 | 8,619,870,647 | 8,939,630,271 | 10,706,229,125 |
| **Value** | 92,993,715,437 | 98,179,003,722 | 119,215,430,000 | 203,219,080,548 | 172,207,650,931 | 168,193,057,422 | 196,117,045,944 |
| **Sugar** | | | | | | | |
| **Quantity** | 1,454,620,808 | 1,008,751,415 | 2,073,189,302 | 1,790,887,295 | 2,274,388,030 | 2,070,141,533 | 2,375,259,290 |
| **Value** | 14,911,058,113 | 13,797,282,101 | 22,380,122,942 | 19,224,307,817 | 29,895,290,932 | 35,735,565,526 | 45,823,330,619 |

Source: Department of Commerce, Thailand

Figure 2.2: Rice price (FOB) at Bangkok, Thailand from 1 January 2008 to 24 December 2008




Source: DataStream download on 5th January 2009

ing price in the futures market as the indicator of price in the cash market. In contrast, the rice futures price in AFET is not the instrument of price discovery because the Thai government always intervenes in the cash market of rice. That means all risks are not diversified. Instead, the Thai government alone carries this risk. The government loses money via subsidies or price guarantee projects; they replenish lost income through taxes or government budgeting. We might call this situation a "National Risk".

As can be seen from Figure 2.2, which shows the futures price of rice, there are some periods where the price remains constant. This is the effect of price assurances by the Thai government. Farmers or exporters do not participate in the futures market because they know what the price will be. Furthermore, most guaranteed government prices are higher than the market price. Therefore, the rice futures prices in AFET do not reflect updated prices from the markets.

The income of Thai rice farmers has been transparent because of price assurance projects, but the Thai government or other exporters still encounter price uncertainty, especially with international prices. Due to Thailand's position as a world-leading exporter of rubber and rice and the high proportion of international trading of agricultural products, the Thai government and exporters must consider the agricultural price within the international framework.

To summarise, this thesis examines the risk management of Thailand's agricultural exports.

However, this thesis cannot employ the futures price from Thailand's futures market for two main reasons. Firstly, there is no liquidity in the futures market. Many transactions do not involve the futures market, as they prefer to trade physical assets in the cash market. This preference causes the data to be not truly reflective of the need. The second reason is the immaturity of the futures markets in Thailand, due to a lack of a management system or adequate controls. Thus, the other active agricultural futures markets should be considered in order to obtain the best futures prices.

# Chapter 3

# Literature Review

This section reviews research papers related to risk management, which incorporate a volatility process and consider risks in agricultural risk management. The important characteristic of agricultural commodities is a seasonality pattern. This seasonal effect is applied in the price risk management research and also the rainfall insurance modelling study for improving estimation performances.

## 3.1 Agriculture Risk Management

Risk is defined as a possibility of loss and the consequences of that loss in the future. Even though there are currently many methods of forecasting future occurrences, there can be no definite assurances. Uncertainty about the future is a serious financial issue that may result in considerable losses or even bankruptcy. There are many sources of risk such as, stock prices, interest rates, exchange rates, weather and political issues.

Many techniques or financial instruments have been introduced to assist firms in minimising their risks to an optimal risk level. Risk is categorised into two types: systematic and nonsystematic. The classical portfolio theory suggests that nonsystematic risks are eliminated by holding multiple assets which is called diversification strategy. For example, Galvan and Plourde (2010) demonstrate that the risks of an energy portfolio can be reduced through diversifying, but it will not produce any considerable returns if the investor applies buy-

and-hold strategies. The portfolio performance was determined by using a mean-variance approach. Their empirical studies on time-varying information strategies indicate that the dynamic strategies on portfolio spanning could not illustrate any improvement on diversification.

Mohan (2007) illustrates the benefit of using the coffee put options in LIFFE and NYBOT, as employing the most world-active exchange market reduces the cost of a producer price, which, in turn, implies a higher gain from this risk management approach. Limiting losses of options is accomplished through the option premium , and the gain arises from the coffee price at the maturity date. This seems like diversification in different asset classes. However, the diversification in production does not show any gain for coffee producers. Mohan argues that coffee specialists would gain a higher profit from niche productions and the economics of the sale than a diverse-planting farmer. In addition, Mohan suggests that if the world leading exchange market is able to establish their branch in the leading production country, an advantage would be gained in both producers' and participants' exchange markets because of cost reduction and high accessibility.

As rapid environmental changes have affected production, it has led to the general acceptance of a unique risk. Hanson et al. (2004) point out that the unique risk has been addressed in organic agriculture. They conducted a survey of grains and organic cotton farms by using the focus group method between 2001 and 2002. The general risks for farmers such as production risk, price risk and policy risk were found; moreover, the uncertain risk, of genetically modified organisms (GMO), was pointed out in group discussions. Organic farmers employ many approaches to managing their risks, like marketing strategy and crop diversification. However, crop insurance is a desirable financial product for organic farmers to hedge their market and yield risks. Moreover, Hess et al. (2004) documents that there is a high demand for weather risk based financial instruments, but the creditability of the insured must be constructed. Previously, the traditional weather hedge approach of crop diversification was very popular because of a lack of weather insurance contracts and expensive premiums related to moral hazard and adverse selection. However, the traditional weather hedge's approach through crop-diversification in planting remains popular in developing countries. Five

criteria are suggested which would develop new risk management methods in emerging markets through reliable weather data, good regulatory frameworks, risk transfer mechanisms, well-known facilitators and a large enough number of insurers and financial institutions.

The level of risk perception and the awareness of financial management may affect risk management action and financial instruments. For example, Just, Wolf and Zilberman (2003) state that farmers' reaction to risk management depends on an assessment of the available information, and their experiences are an important factor in enhancing their risk management performances. Data from the USDA was used to support their analysis because it is a reliable source of information. However, the data are not user-friendly and would require special training to extract useful information. In addition, Meuwissen et al. (2001) conducted a study on farmers' perception of risk and risk management in the Netherlands. The empirical results show that insurance is less important to farmers who use crop diversification.

## 3.2 Volatility

### 3.2.1 Volatility Models

Volatility forecasting is a fundamental element of investment strategy, option pricing and risk management. Volatility forecasting is the indicator by which the price changes in the financial market. Poon and Granger (2005) conducted a volatility review of the last 20 years. They state that there are 4 main categories to the volatility model, namely a historical volatility model, a model in Autoregressive Condition Heteroskedasticity (ARCH) class, a stochastic volatility model and an implied volatility model. The last model is completely different from the time-series models. Comparisons of 93 volatility studies indicate that the implied volatility model provides the best performance, following by the GARCH and the historical volatility model. However, the performance of the volatility model is not dominated by one model according to the mixed results of the 93 volatility studies.

The four volatility models selected by Poon and Granger are popular amongst analysts and researchers because of the characteristics of each model. The historical volatility model is

a function of previous volatility and past changes in asset prices. The implied volatility model is derived from the expected future volatility and is determined from the option price on the underlying asset. The stochastic volatility model assumes the asset price process is random and the underlying volatility is not constant. The autoregressive conditional heteroskedasticity (ARCH) class has been studied since its introduction by Engle (1982). The conditional variance is a function of previous error terms, as seen in the formula below:

$$\sigma_t^2 = \omega + \Sigma_{i=1}^{j} \alpha_i \varepsilon_{t-1}^2 \tag{3.1}$$

where $\sigma_t^2$ is the conditional variance at $t$, $\varepsilon_{t-1}$ is the previous error term, $\omega$ is the constant, and $\alpha$ is the coefficient of the previous error term. of A useful generalisation of ARCH, what is known as GARCH, was proposed by Bollerslev (1986). This model allows the conditional variance to depend on its own lags and the previous squared errors.

$$\sigma_t^2 = \omega + \Sigma_{i=1}^{q} \alpha_i \varepsilon_{t-1}^2 + \Sigma_{j=1}^{p} \beta_j \sigma_{t-1}^2 \tag{3.2}$$

where $\sigma_{t-1}^2$ is the previous conditional variance,$\varepsilon_{t-1}$ is the previous error term $\alpha$,and$\beta$ are the coefficients. In addition, the GARCH model has been extended via numerous variants, such as non-linear GARCH (NGARCH), exponential GARCH (EGARCH), and Glosten, Jagannathan and Runkle GARCH (GJR-GARCH), all of which are presented in the following paragraphs.

The non-linear GARCH (NGARCH) by Engle and Ng (1993) is used to estimate the leverage effect to volatility process. The specification NGARCH (1,1) is given by

$$\sigma_t^2 = \omega + \alpha \left(\varepsilon_{t-1} - \theta \sigma_{t-1}\right)^2 + \beta \sigma_{t-1}^2 \tag{3.3}$$

where $\sigma_{t-1}^2$ is the previous conditional variance,$\varepsilon_{t-1}$ is the previous error term $\alpha$,$\beta$ and$\theta$ are the coefficients.The specification of exponential GARCH (EGARCH) is proposed by Nelson (1991) in order to capture the asymmetric effect. The EGARCH (1,1) is given by

$$\log \sigma_t^2 = \omega + \beta \left( \log \sigma_{t-1}^2 \right) + \gamma \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \alpha \left[ \frac{\mid \varepsilon_{t-1} \mid}{\sigma_{t-1}} - \sqrt{\frac{\varepsilon_{t-1}}{\sigma_{t-1}}} \right] \tag{3.4}$$

where $\omega, \gamma$and $\alpha$ are coefficients. The GJR-GARCH by Glosten, Jagannathan and Runkle (1989) is also used to estimate the asymmetric effects of negative and positive shocks. The GJR-GARCH (1,1) is shown below

$$\sigma_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 + \delta \varepsilon_t^2 I_{t-1} \tag{3.5}$$

where $I_{t-1}$ is a dummy variable which takes a value of 1 when $\varepsilon_{t-1} < 0$ and value of 0 otherwise.

Many researchers apply the ARCH volatility model in the financial market. Zlatko (2007) investigates the behaviour of stock returns in an emerging market, namely the Macedonian Stock Exchange, which began trading in 1996. Zlatko offers the stylized facts of the stock daily return's time series, and then analyses the data, which represents volatility clustering, mean reversion and high kurtosis. The optimal volatility specification is arrived at through comparing the performances of the different volatility economic models, which are GARCH, GJR-GARCH, Threshold GARCH (TGARCH) and Power GARCH (PGARCH). The results indicate that GARCH outperforms others models in terms of in-sample and out-of-sample.

There is a significant amount of research in the commodity field, for instance, Oglend and Sikveland (2008) study the weekly price volatility movement of Norwegian salmon. The motivation behind this research is to understand the volatility behaviour of Norwegian salmon which would be beneficial for pricing forward and futures contracts, and the futures market for salmon in Norway. Their results indicate that a volatility term would be better described by the GARCH model. Therefore, risk averse investors would appreciate the hedge as much as they can.

Huang et al. (2009) studied the weekly price volatility and volatility specification of log broiler and colour broiler chicken prices in Taiwan between 1995 and 2007. This period covers before, during and after Taiwan joined the WTO. There are many significant effects arising

from Taiwan's participation. The experiments display a non-stationary process of log broiler and colour broiler chicken prices. Furthermore, volatility seems to persist over the whole period, and negative shock causes an increased volatility. GARCH, GJR and EGARCH are all significant volatility models in this context.

Additionally, there are many research papers which have investigated volatility not only as a spot price but also as a futures contract price, especially in agricultural commodities. Agricultural commodity prices are subject to considerable variability. Understanding their volatility patterns is important to properly interpreting the time series of futures prices and making risk management decisions.

For example, Du and Wang (2004) has investigated the daily wheat futures price movement from May 2000 to 2002 in China Zhengzhou Commodity Exchange (CZCE) by modelling three different variance forecasting styles. The first model is the autoregressive moving average (ARMA) model that assumes a constant variance. The other two models, the autoregressive conditional heteroskedasticity (ARCH) model and the generalized ARCH (GARCH) model, follow the time-varying volatility in the data. The mean term is similar in all models; the difference is the volatility term. There are two experiments in this research that calibrate and forecast volatility.The model comparison results present many outcomes, depending on the criteria used, namely AIC and SBC. The GARCH and ARCH models are better performing than the AR model. In addition, GARCH fits the data best in terms of AIC and SBC; on the other hand, the ARCH model outperforms GARCH in terms of significant coefficients' criteria. For the second experiment, the results of out-of-sample forecasts indicate that GARCH is more currently improving in forecast than the ARCH and AR in the out-of-sample test , based on the test of the forecasting default rate comparing with the true price.

Furthermore, Singh (2007) investigate the daily fabric cash (spot) price variability before and after the introduction of futures trading (1988-1991 and 1992-1997) in Indian markets using the multiplicative dummy variable model as follows:

$$lnV_t = a + blnP_t + \sum_{j=1}^{11} c_i d_{jt} + a^* D^* + b^*(D^* lnP_t) + \sum_{j=1}^{11} c_i^*(D^* d_{jt}) \tag{3.6}$$

where $a, b, c, a^*, b^*$and $c^*$are coeffients, $P_t$ is the logarithm of jute price, $d_j$ is the monthly dummy variableand $D^*$ is the additional dummy variable for 1992-97. Therefore, the volatility is a function of the constant variable, dummies of monthly seasonality and dummies for entire 1992-1997 period. The empirical results point out that futures trading has reduced the price volatility in the hessian cash market. In addition, Ranjan (2005) also studies the implication of the futures market in India. A simple volatility model is employed with soya oil futures contracts: he finds a significant reduction in seasonal price volatility after introducing the futures market, although there is a negligible decrease in daily price volatility.

Volatility is used to quantify the risk of a financial instrument over the time. For example, Hayakawa and Kimura (2009) studied the effects of the exchange rate risk (volatility) on the export value of countries in East Asia within region and also the other regions. Monthly data is used in this experiment. The experiments illustrate various effects; for instance, the high exchange rate volatility makes fewer international trades, especially between East Asian countries. Their empirical study shows the intermediate goods have higher affect from the exchange rate volatility than the finished goods. Liu et al. (2008) estimates VaR in the Chinese copper market with the purpose of measuring risk in the spot and futures market by using the TGARCH and GARCH models. VaR is the main risk management tool for controlling volatility. Their results indicate that there is a long running tendency between the spot and futures market; moreover, volatility clustering and significant conditional heteroskedasticity are discovered in both markets.

In addition, Doran and Ronn (2008) claim that the daily market price of volatility risks in the energy commodity sector, namely heating oil, natural gas and crude oil, have negative value and significance. They illustrate an approach to estimating volatility risks that differs from Black-Scholes (1973) implied volatility and realized term volatility. Doran's and Ronn's models also incorporate the seasonality pattern and the jump component. Their results indicate that seasonality is a very important component in the volatility risk premium for natural gas.

For volatility modelling, many stylised facts are introduced in the time varying volatility approach. Koekebakker and Lien (2004) claim that agricultural prices exhibit fat tail distribu-

tions. They proposed an option pricing model, which incorporates jump-diffusion process and time varying volatility. This volatility specification consists of a calendar time function (seasonal pattern) and time to maturity (maturity effect). The performance of this model is better that the model without these two features and the jump component. They also suggest that omitting time-dependent volatility and jump effect cause inaccurate option prices. Richter and Sorensen (2000) claim that both the soybean spot price and the volatility of soybean futures and option prices from the Chicago Board of Trade exhibit a seasonal pattern.

In addition, Karali and Thurman (2010) construct the daily future price volatility model as a linear function. Firstly, they identify the related factors which affect price movement, and then attempt to generate a volatility model incorporating seasonality variable, inventories variable, lagged volatility and quadratic function of time (to delivery and calendar time). Agricultural futures contracts' prices in the U.S. of corn, soybean, wheat and oats are examined in the composed volatility model. Their experiment found that price volatility is time varying, especially increasing in the summer months before the harvesting period. Furthermore, it was shown that as the time to maturity decreased, the volatility increased, and a movement which is called the Samuelson effect. Their research found a negative relationship between the inventory and price volatility: there was a high volatility when the inventory trend was small quantities; however, after the harvest there was low volatility.

Myers and Hanson (1993) compare the option pricing of the original Black (1976) model and their new model which charts the volatility of the daily futures price process as a GARCH model. The results show that the GARCH option pricing model presents a better outcome than the Black model. However, the estimated variance terms do not have the same pattern in every commodity or agricultural product, as has been found by Beck (2001). Beck claims that there are differences in the stochastic behaviour of commodity price volatility, for example, ARCH has been found in storable, but not in non-storable commodity data.

The other advanced application of volatility modelling is included in convenience yield modelling. Convenience yield is a benefit to the physical holder of a commodity as defined by Working (1948,1949) and Kaldor (1939). Chen et al. (2008) studied the relationship between

volatility and the spread of two different time maturities of crude oil futures contracts in the NYMEX crude oil market. Their results indicate that convenience yield behaves like an American call option. That implies that the information content of convenience yield is the volatility behaviour. Therefore, they computed the convenience yield by using the Copula-based American GARCH call option pricing model. They propose that there will be an improvement in risk management and derivative pricing by including volatility behaviour in the convenience yield model. Their finding is similar to Biagini and Bjork (2007) which examines the relationship volatilities and the calendar spread of two commodities: gasoline and heating oil.

Understanding the dynamics of volatility is important for professionals in hedging and risk-management. For instance, Samuelson (1965) states that the volatility of agricultural futures prices increases during the time to maturity. Trolle and Schwartz (2009) expand a tractable stochastic volatility model for pricing commodity derivatives. They conjectured that when volatility is stochastic, volatility is composed of spanned and unspanned volatilities. Spanned volatilities are replicated by using financial instruments, such as futures or options. Most of the equilibrium models assume that volatility is spanned by the futures contract. However, then the concern should be the unspanned volatility, as this is not covered by the futures contract. Thus, Trolle and Schwartz develop the pricing model for commodity derivatives, including the unspanned stochastic volatility, through the Heath, Jarrow and Morton (1992) framework. The experiments point out that a two-volatility factors model outperforms at capturing the variation in implied volatility in option, especially in terms of pricing short-term and medium-term options. Finally, they raise an interesting issue for further research, which is the importance of unspanned stochastic volatility for an agricultural market.

### 3.2.2 Seasonality and Weather Risk

The second distinctive issue for agriculture is seasonal effect and weather risk management. Weather is a major factor causing unpredictable production. This thesis contributes significant

research on rainfall modelling in chapter 5; therefore, the related previous studies on this topic will be further explained later. However, the main ideas and useful literature are described in the following.

Many times series exhibit a cycling movement known as seasonality or periodic variation. For example, agricultural data usually exhibits a seasonal production pattern, related to weather, climate and harvest. Roberts (2001) states that the production of agricultural products has a distinctive commodity price behaviour, due to a seasonality pattern in production. Therefore, seasonality is a one of the empirical characteristics that distinguish some agricultural commodities from the other financial assets. Felkner, Tazhibayeva and Townsend (2009) claim that rice production and the welfare of farmers in Srisakat province, Thailand, are considerably effected by climate change. Decision makers should take the climate into account in order to efficiently and effectively intervene. They compare the rice yield change from an economic model that incorporates soil science variable, weather simulator and global climate model, with the global climate model, and predictions simulated by the DSSAT (Decision Support System for Agro-technology Transfer) programme. This programme requires 30 indicating variables, such as root density and the amount of leaves per stem, to evaluate rice's growth. It excludes a labour factor and non-systematic risks that lead to overestimation. The data was gathered during weather with normal, high and low $CO_2$ emissions. The high emission simulates a decrease in rainfall but an increase in temperature. These results illustrate that changing weather factors lead to a decrease in yield, especially when estimated by DSSAT when the low emission scenario is assumed. On the other hand, a major yield was found when computed by the economic model with a high emission scenario.

Stifel and Randrianarisoa (2006) state that seasonality is exhibited in the price series and volatility process of agricultural products, such as rice, maize and cassava in Madagascar. Using the seasonal multi-market model, they discovered the impact of Madagascan agricultural policy. The market is divided into two groups: urban and rural. The outcomes indicate that the policy is concerned with how seasonality will improve household income levels. Moreover, their findings suggest that for the improvement of the quality of life in a developing country,

and specifically in Madagascar, there should be an investment in rural infrastructure and in commercial food storage.

To confirm this idea of seasonality in agricultural commodities, Tomek and Peterson (2001) also suggest that the demand or supply of agricultural products is a major cause of seasonality in spot prices. For example, most major crop production follows a seasonal pattern but marketing occurs throughout the remaining year. This pushes the price up during the growing period but leads to a relatively lower price at harvest time. The work of Karali and Thurman (2010) confirms this. By studying the determinants of daily price volatility in the U.S. agricultural futures price through volatility experiments, they found seasonal and Samuelson effects present in the price process. Samuelson (1965) introduces the theoretical concept of the relationship between the futures price volatiity and time to maturity. His empirical study demonstrates that the volatility of futures prices volatility increases as the futures contracts approach to maturity date. This property is known as the "Samuelson Effect".

Lucia and Schwartz (2002) introduce the mean reverting derivative pricing model composed by Schwartz (1997) and incorporate it with a seasonality component for electricity prices. They firstly examined the behaviour of electricity prices from Nordic Power Exchange. Spot and futures prices were then analysed. The experiment indicated that the seasonal systematic pattern throughout the year currently showed in the spot and futures price. This lays the groundwork for generating a model that can capture the seasonal pattern.

Cartea and Figueroa (2005) present the closed-form model of a mean reverting jump diffusion model with seasonality. They combined three important characteristics, mean reverting, jump diffusion and seasonality, of a commodity, electricity. Electricity prices in the English and Welsh markets are the data for this experiment that exhibits all three considerable features. A spot-base model and a forward-based model are analysed in order to obtain the closed form model and test the robustness of these models. The results indicate that the new model improved the prediction spot and futures price of electricity pricing.

Borovkova and Geman (2007) claim that agricultural prices exhibit a seasonal pattern driven by seasonal supply. The upward price movement is always shown before the harvest.

They also suggest that the other commodity prices, such as gas and electricity, exhibit the seasonality.

Styger and Heymans (2008) introduce the approach to test for the presence of stochastic or unobserved seasonality versus a deterministic seasonality. They employed white and yellow maize prices from the South African market to test this. The results use no significance statistic test; however, the graphics illustrate a strong correlation between the forecast and the actual series. They also suggest that the understanding of the seasonal component in the agricultural price's process is important for traders of agricultural pair trading portfolios. There are many research papers that relate to the agricultural product, for example, Kenyou et al (1987) analysed grain price, Malick and Ward (1987) studied frozen concentrated orange juice and Netz (1996) investigated the seasonal effects in corn. Their empirical results confirm the existence of seasonality.

Roberts (2001) claims that a seasonal volatility is a significant component of the option pricing model. He employs a polynomial expansion, ending at the point of contract expiry to represent the seasonal pattern. The comparison results indicate that the root mean squared error (RMSE) between the acture price and forecast price from seasonal volatility reduces by 15 per cent to 18 per cent when compared with non-seasonal GARCH. Hudson and Coble (1999) suggest that the seasonality pattern is in a cotton volatility price, and it is also an important component for understanding the price risk management scheme. Richter and Sorensen (2000) claim that agricultural products always exhibit seasonality patterns in price level and volatility. They created an agricultural stochastic volatility model and also estimated the model's parameters with a soybean futures price. Soybean futures and option prices from CBOT from the period October 1984 to March 1999 are employed as a set of sample data. Their results confirm that seasonal components consist of both volatilities and convenience yields.

There are many research papers related to seasonality and volatility. The stochastic volatility is introduced when researchers attempt to relax the assumption of a constant volatility, especially with agricultural products. For example, Fackler (1986) contributes to the seasonal

effects in volatility by substituting a Fourier expansion for the intercept of the GARCH volatility equation. Robert (2001) also investigates the effects of deterministic volatility modelling and various conditional distributions of volatility. The experiment indicates that seasonal volatility is a significant component in option pricing by reducing the pricing error when compared with the standard GARCH model.

To conclude, as explained above, there is much research related to commodity pricing and risk management but few studies are concerned with agricultural commodities. We have already explained the importance of the agricultural price, especially in food and in the raw materials for consumption goods. Hence we focus on price risk and weather risk for agricultural commodities; within this the seasonality pattern in agricultural commodities prices is investigated. In addition, as the futures contract price is commonly used in many studies, this thesis will investigate the features of an important parameter called convenience yield in the future derivative pricing approach. More detail on the convenience yield is given in Chapter 5.

# Chapter 4

# Price Risk Modelling for Agriculture Commodities - Effects of Asymmetry and Seasonality

## 4.1 Introduction

Our objective is to model the return volatility on several agricultural commodities, as the volatility of return is an essential element in derivative pricing and risk management. Agricultural products' price risk trends have distinctive features from other financial products.

Therefore, initially, a time series analysis of the individual agricultural commodities, rubber, rice and white sugar, were studied in order to obtain the stylised facts of price behaviour. The stylised facts of these agricultural commodities were also examined and then incorporated into a volatility model which addresses both asymmetry and seasonality.

The proposed volatility model has been modified from the GJR-generalized autoregressive conditional heteroskedasticity (GJR-GARCH) model, which is used to evaluate the volatility behaviour of agricultural commodities in this study. Extensions of the GJR-GARCH model are generated by including the asymmetry and seasonality in mean equations and volatility process. The results indicate that the seasonality components exist in both mean equations and the volatility process.

In addition, in order to capture the high kurtosis found in the data, we also investigated the use of several error distribution models: Gaussian, Standardised-t and the Generalised

error distribution (GED). We compared the forecasting performances of the proposed models using Value-at-Risk to evaluate the relative accuracy of these models.

The remainder of this chapter is structured as follows. Section 4.2 contains a crucial literature review of agricultural volatility, where in the main objectives of this research are described. Section 4.3 explains the characteristics of the data, which was collected from the most active agricultural commodity markets in the world. Section 4.4 provides the volatility model, which accommodates day-of-a-week and yearly seasonality and demonstrates asymmetric variables; moreover, the alternative error distributions, namely Standardised-t and the Generalised error distribution are considered. In addition, the method of one-day and five-days horizon value-at-risk estimates are described. In section 4.5, the estimated parameters and the applications of VaR are presented; the validity of the composed model is tested by a binomial test and an independence test. Finally, the conclusion of this analysis will be presented in section 4.6.

## 4.2 Literature Review

The seasonality of agricultural products is likely to occur due to production periods and weather. Roberts (2001) states that the production of agricultural products has a distinct effect on commodity price behaviour due to its seasonal nature. The results indicate that the forecast pricing error of seasonal volatility reduces by 15 per cent to 18 per cent when compared with GARCH. Hudson and Coble (1999) suggest that a seasonality pattern is found in cotton volatility pricing, and seasonality is also an important component in understanding price risk management. Richter and Sorensen (2000) claim that agricultural products always exhibit a seasonality pattern in price level and volatility. They compose a stochastic volatility model and also estimate its parameters with a sample of soybean futures. Soybean futures and option prices from CBOT in the period October 1984 to March 1999 are employed as a set of sample data.

Stifel and Randrianarisoa (2006) state that significant seasonality is exhibited in price series and volatility processes of agricultural products, such as rice, maize and cassava in

Madagascar. Tomek and Peterson (2001) also suggest that the variation in demand or supply for an agricultural product is a major cause of seasonality in spot prices, which is similar to the findings of Karali and Thurman (2010). Furthermore, Borovkova and Geman (2007) claim that the seasonal pattern of agricultural prices is driven by seasonal supply. Upward price movements always occur before the harvest. They also suggest that other commodity prices, such as gas and electricity, display seasonality. There is an abundance of research papers related to agricultural products, for example, Kenyou et al. (1987) analyses grain price and Malick and Ward (1987) studies frozen concentrated orange juice. Their empirical results confirm the presence of seasonality.

As this chapter employs the nearest futures price as a spot rate which is traded on international organized futures markets, another important seasonal effect in the traded price is the day-of-the week effect. Investors trading in organized markets understand there is a cycle pattern for returns during the week: for instance, Wong, Hui and Chan (1992) state that a significant negative return is usually detected on Monday and a high return on Friday in many stock markets, such as the United States, Canada, Singapore, Malaysia and Hong Kong. Taiwan does not indicate any significant day-of-the week effect in their stock market. Kohers et al. (2004) document that the lowest returns could be found on Monday in many markets with the exception of Japan and Australia wherein it is present on Tuesday. However, the usefulness of the day-of-the-week in trading strategy is gradually eliminated when the market becomes a strong-form efficienct market.

Day-of-the-week effect in volatility is also studied, for example, Berument and Kiymaz (2001) investigate the effect of both returns and volatility on the S&P 500. Their results indicate a similarity with Kohers et al. (2004) and Wong, Hui and Chan (1992) in that the lowest return is found on Monday. However, Berument and Kiymaz (2001) also concluded using GARCH that Friday and Wednesday evidenced the highest and lowest volatility. Furthermore, they extended their determination to the international market, including, for example, Germany, Japan, the United Kingdom, Canada and the United States. The day-of-the-week effect in return and volatility is still significant to these markets; however the timing of the

highest and lowest volatility during the week varies between countries (see Kiymaz and Berument, 2003). Most of the current research focuses on the stock market. There are few studies which investigate the day-of-the week effect in the agricultural market during the last decade.

With regard to the volatility model, Poon and Granger (2005) conducted a research review of volatility studies undertaken in last 20 years. Comparisons of 93 volatility studies indicate that the implied volatility model provides the best volatility forecasting performance. This was determined by examining the results of the S&P 500 index between 1 February 1983 and 31 July 2003, against the implied volatility, the GARCH and the historical volatility models. However, the performance of volatility forecasting is not dominated by one model, according to the mixed results in many papers. Several authors apply the ARCH-family volatility model in the financial market, particularly in the commodity market. Examples are Oglend and Sikveland (2008) and Huang et al. (2009).

This chapter aims to demonstrate the asymmetric effect on the volatility process, which allows for an test of the interaction between the volatility and the return shocks. For example, the bad news in the financial market is normally represented by a negative residual that would causes higher volatility than the good news as represented by the positive residual. Martens et al. (2009) composed a volatility model by including asymmetric , seasonality and macroeconimic effects on announcements for daily S&P 500 index. Their applications in value-at-risk of proposed model are more accuracy than the model excludes these variables. There are many empirical studies that show volatility increases are highly related to bad news, especially in the equity market as in Bekaert and Wu (2000).

However, for agricultural prices, Huang et al. (2009) study the effect of broiler and colour broiler chicken prices in Taiwan after Taiwan joined the World Trade Organization (WTO). GARCH, GJR-GARCH and EGARCH are used to estimate volatility. The key findings in GJR-GARCH show that the asymmetric coefficient is significantly negative. This finding is similar to the summary by Geman (2005). The positive correlation between commodity price shock and its volatility is found in commodity because these negatives are strongly connected to the level of storage.

## 4.3 Data and Methodology

### 4.3.1 Data

We describe the analysis of the time series of three commodity price series: rubber, white sugar and rough rice. We investigate the presence of the effects discussed in the previous section, namely asymmetry in volatility, and seasonality. All of the data included below is from DataStream.

The nearest maturity daily futures prices are collected as a proxy for the spot prices of agricultural products from the most active trading market for each commodity because of no liquidity and the immaturity of the Agriculture Futrue Exchange of Thailand (AFET) market. Firstly, the rubber future settlement prices at Tokyo Commodity Exchange set extends over the period 1st January 1991 – 30th December 2011. There are 5479 daily observations which are recorded on every weekday. Secondly, the white sugar future settlement prices at Euronext.liffe, London are in the period 1st January 1996 to 30th December 2011 which consists of 4175 daily observations. Finally, the 2870 daily observations of rough rice future settlement prices at Chicago Board of Trade in the period 1st January 2001 to 30th December 2011.

Table 4.1 provides the summary statistics of a daily logarithm return of the three commodities. The stylised facts of each daily return are observed. Our models include the weekly seasonality effect because trading behaviours in exchange markets cause price patterns, as shown in Berument and Kiymaz (2001). For average daily return, the highest rubber average return is on Monday and the lowest average return is on Wednesday. White sugar returns have a peak on Friday, and experience a low on Monday. The mean rough rice returns are all positive except on Tuesday. The maximum return occurs on Friday. In addition, the excess kurtosis of all samples is significantly high which implies a fat-tailed distribution.

Table 4.1: Stylised facts for three commodities by day of the week

| | Days | N | Max | Min | Mean | SD. | Skewness | Excess Kurtosis |
|---|---|---|---|---|---|---|---|---|
| Rubber | All | 5479 | 0.1058 | -0.2573 | 0.0001 | 0.0212 | -0.6217 | 6.4769 |
| (Tokyo Commodity Exchange :TOCOM) | Monday | 1095 | 0.0999 | -0.1408 | 0.0012 | 0.0224 | -0.1509 | 3.9486 |
| Data Period | Tuesday | 1096 | 0.0906 | -0.0883 | -0.0003 | 0.0198 | -0.2231 | 2.1387 |
| 1st January 1991 – 30th December 2011 | Wednesday | 1096 | 0.0736 | -0.0803 | -0.0013 | 0.0205 | -0.2811 | 0.8967 |
| | Thursday | 1096 | 0.1058 | -0.2573 | 0.0002 | 0.0233 | -1.7251 | 15.8366 |
| | Friday | 1096 | 0.0675 | -0.1242 | 0.0008 | 0.0197 | -0.2991 | 2.3786 |
| Rough Rice | All | 2870 | 0.1368 | -0.2192 | 0.0003 | 0.0183 | -0.2253 | 9.8979 |
| (Chicago Board of Trade: CBOT) | Monday | 574 | 0.0782 | -0.0770 | 0.0012 | 0.0176 | 0.5501 | 2.2436 |
| Data Period | Tuesday | 574 | 0.1368 | -0.0910 | -0.0013 | 0.0188 | 0.4597 | 6.2987 |
| 1st January 2001 to 30th December 2011 | Wednesday | 574 | 0.0926 | -0.0736 | -0.0001 | 0.0191 | 0.1186 | 2.3342 |
| | Thursday | 574 | 0.0762 | -0.2192 | 0.0001 | 0.0189 | -2.4416 | 31.3426 |
| | Friday | 574 | 0.0759 | -0.0467 | 0.0017 | 0.0166 | 0.7162 | 2.2298 |
| White Sugar | All | 4175 | 0.0823 | -0.1705 | 0.0001 | 0.0172 | -1.0268 | 8.9859 |
| (Euronext.liffe, London) | Monday | 835 | 0.0549 | -0.1705 | -0.0008 | 0.0185 | -2.2875 | 15.5110 |
| Data Period | Tuesday | 835 | 0.0598 | -0.1213 | -0.0003 | 0.0177 | -0.7869 | 5.7223 |
| 1st January 1996 to 30th December 2011 | Wednesday | 835 | 0.0787 | -0.0553 | -0.0001 | 0.0157 | 0.4014 | 2.1186 |
| | Thursday | 835 | 0.0823 | -0.1411 | 0.0003 | 0.0173 | -1.0505 | 9.5006 |
| | Friday | 835 | 0.0783 | -0.1172 | 0.0015 | 0.0164 | -0.6826 | 6.9257 |

### 4.3.2 Methodology

#### 4.3.2.1 Volatility Model

As this study aims to improve price risk modelling, the proposed volatility model should be able to forecast with more accuracy than the existing volatility model. From the literature review, the seasonality and asymmetric factors have been found to be the essential components of a volatility model, especially in regards to agricultural commodities. In this proposed volatility model, the returns on agricultural futures prices are calculated first by changing the logarithm used for the daily closing of futures prices. The return can be written as

$$y_t = \ln(P_t) - \ln(P_{t-1}) \tag{4.1}$$

A discrete-time log daily return is assumed for this paper, giving the form of mean equation and the error term process as the following

$$y_t = \mu + \varepsilon_t \tag{4.2}$$

where the error term is a function of the log daily return and the unconditional mean, the GJR-GARCH model is used as an initial volatility model. This volatility process, created by Glosten, Jagannathan and Runkle (1993), is used to capture the volatility clustering and asymmetric effect. The GJR-GARCH is expressed as follow

$$\sigma_t^2 = \omega + \beta\sigma_{t-1}^2 + \alpha_1\varepsilon_{t-1}^2 + \alpha_2 \min(0, \varepsilon_{t-1})^2 \tag{4.3}$$

where $\omega, \beta, \alpha_1 \geq 0$, $\beta + \alpha_1 + \frac{1}{2}\alpha_2 < 1$ and $\alpha_1 + \alpha_2 \geq 0$. These equations are the starting point for the following assumptions. However, the GARCH model is also used as a reference volatility model because the asymmetric parameters might be insignificant in every sample. The GARCH specification is

$$\sigma_t^2 = \omega + \beta\sigma_{t-1}^2 + \alpha_1\varepsilon_{t-1}^2 \tag{4.4}$$

where $\omega > 0$, $\alpha_1, \beta > 0$ and $\alpha_1 + \beta < 1$.

#### 4.3.2.2 Alternative Error Distributions

Due to the fact that the statistical description clearly demonstrates a high kurtosis for the agricultural commodities examined in this study, three assumptions of error distribution are used in this paper: Gaussian, standardised-t and generalised error distribution (GED). Standardised-t and Generalised error distribution (GED) are used in general cases to capture the high kurtosis of our samples. The standardised-t error distribution, as shown in Christoffersen (2003), estimates both the variance and degree of freedom parameters in the formula which follows. All three error distributions will be explained below:

- Gaussian Distribution

$$f_G(\varepsilon_t \mid \sigma_t^2) = \frac{1}{\sqrt{2\pi\sigma_t^2}} \exp\left(\frac{\varepsilon_t^2}{2\sigma_t^2}\right) \tag{4.5}$$

- Standardised-t Distribution

$$f_S(\varepsilon_t \mid \sigma_t^2) = \frac{\Gamma\left[(\nu+1)/2\right]}{\sqrt{\pi\left(\nu-2\right)\sigma_t^2}\Gamma\left(\nu/2\right)} \left(1 + \frac{\left(\frac{\varepsilon_t}{\sigma_t}\right)^2}{(\nu-2)}\right)^{-\left(\frac{\nu+1}{2}\right)} \tag{4.6}$$

- Generalised Error Distribution

$$f_{GED}(\varepsilon_t \mid \sigma_t^2) = \frac{\nu \exp\left(-\frac{1}{2} \mid \frac{\frac{\varepsilon_t}{\sigma_t}}{\lambda} \mid^{\nu}\right)}{2^{\left(1+\frac{1}{\nu}\right)}\lambda\Gamma\left(\frac{1}{\nu}\right)} \tag{4.7}$$

There are several reasons that induced us to select Standardised-t and GED for this study. Firstly, these two capture the characteristics of heavy tails, and the secondly, both become a

Gaussian distribution when either the degree of freedom in standardised-t approaches infinity $\nu \to \infty$ or $\nu = 2$ for GED.

The unconditional long run variance is given by, $\sigma^2 = \frac{\omega}{1-(\alpha_1+\beta+0.5\alpha_2)}$. This is used to initialize the GJR-GARCH variance, and the unconditional long-run variance of GARCH is $\sigma^2 = \frac{\omega}{1-(\alpha+\beta)}$ . All estimations are performed in MATLAB.

The standard errors of the estimated parameters are obtained from the inverse of an information matrix. The information matrix is a variance of the score vector which can be written as equation 4.8. In addition, the information matrix of the maximum likelihood can be calculated by multiplying the Hessian matrix by -1 (Johnston and DiNardo, 2007. pp.143-143) as

$$I(\theta) = E\left[\left(\frac{\partial l}{\partial \theta}\right)\left(\frac{\partial l}{\partial \theta}\right)'\right] = -E\left[\frac{\partial^2 l}{\partial \theta \partial \theta'}\right] \tag{4.8}$$

The Hessian matrix is written as follows

$$E\left[\frac{\partial^2 l}{\partial \theta \partial \theta'}\right] = \begin{bmatrix} \frac{\partial^2 l}{\partial^2 \theta_1} & \frac{\partial^2 l}{\partial \theta_1 \partial \theta_2} & \cdots & \frac{\partial^2 l}{\partial \theta_1 \partial \theta_k} \\ \frac{\partial^2 l}{\partial \theta_2 \partial \theta_1} & \frac{\partial^2 l}{\partial^2 \theta_2} & \cdots & \frac{\partial^2 l}{\partial \theta_2 \partial \theta_k} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial^2 l}{\partial \theta_k \partial \theta_1} & \frac{\partial^2 l}{\partial \theta_k \partial \theta_2} & \cdots & \frac{\partial^2 l}{\partial^2 \theta_k} \end{bmatrix} \tag{4.9}$$

The estimation initially processes the condition variance equation using the log likelihood function. The Gaussian likelihood specification is

$$l_t = \frac{1}{\sqrt{2\Pi\sigma_t^2}} \exp\left(\frac{y_t^2}{2\sigma_t^2}\right) \tag{4.10}$$

and the joint likelihood is

$$L = \prod_{t=1}^{T} l_t = \prod_{t=1}^{T} \frac{1}{\sqrt{2\pi\sigma_t^2}} \exp\left(\frac{y_t^2}{2\sigma_t^2}\right) \tag{4.11}$$

The common method for calibrating the parameters is to maximize the likelihood function. However, the usual approach which is more convenient, estimating the parameters by

maximizing the logarithm of likelihood function (Christoffersen, 2003). The maximization of the logarithm likelihood function is

$$\max \ln L = \max \Sigma_{t=1}^{T} \ln (l_t) = \max \Sigma_{t=1}^{T} \left[ -\frac{1}{2} \ln (2\pi) - \frac{1}{2} \ln \left( \sigma^2 \right) - \frac{1}{2} \frac{y_t^2}{\sigma_t^2} \right] \tag{4.12}$$

This approach is also applied for Standardised-t and GED.

#### 4.3.2.3 Seasonality in the Mean and Volatility Model

Extending the conditional volatility model from the GJR-GARCH is starting with the inclusion of day-of-the week and yearly seasonality. This extended model captures the effects of trading activity in the exchange market and the yearly seasonality, which shows the growth pattern of agriculture. The modelling approach begins with the standard model, GJR-GARCH, and then includes the weekly and yearly seasonality components. The trigonometric function introduced by Hanna,Terry and Tuckwell (1970) is used to represent the seasonality. Hence, a seasonal volatility model is represented in the form of

$$\sigma_t^2 = \omega + \beta \sigma_{t-1}^2 + \alpha_1 {\varepsilon_{t-1}}^2 + \alpha_2 \min (0, \varepsilon_{t-1})^2$$

$$+ \max(0, (\Sigma_{vwk=1}^{2} \left[ \gamma_{vwk} \cos \left( \frac{2\pi kt}{5} \right) + \varphi_{vwk} \sin \left( \frac{2\pi kt}{5} \right) \right]$$

$$+ \Sigma_{vyk=1}^{vyk*} \left[ \gamma_{vyk} \cos \left( \frac{2\pi kt}{260} \right) + \varphi_{vyk} \sin \left( \frac{2\pi kt}{260} \right) \right])) \tag{4.13}$$

where

$$\begin{aligned} \varepsilon_t \quad = \quad & y_t - (\mu + \Sigma_{mwk=1}^{2} \left[ \gamma_{mwk} \cos \left( \frac{2\pi kt}{5} \right) + \varphi_{mwk} \sin \left( \frac{2\pi kt}{5} \right) \right] \\ & + \Sigma_{myk=1}^{myk*} \left[ \gamma_{myk} \cos \left( \frac{2\pi kt}{260} \right) + \varphi_{myk} \sin \left( \frac{2\pi kt}{260} \right) \right]) \end{aligned}$$

in addition, the subscript of the parameters indicates a different seasonality and mean

function in the model. $\gamma_{vwk}$ is the parameter of weekly seasonality in volatility, $\gamma_{vyk}$ is the parameter of yearly seasonality in volatility, $\gamma_{mwk}$ is the parameter of weekly seasonality in mean, and $\gamma_{myk}$ is the parameter of yearly seasonality in mean. The optimal harmonics of yearly seasonal parameters in volatility are chosen by the Akaike Information Criteria (AIC). There are two harmonic optimal weekly seasonal parameters in trigonometric terms representing the price movement during the week.

The conditional variance cannot be negative. Therefore, the restriction of the non-negative value of the sum of the trigonometric terms is achieved by taking the maximum of the seasonal components of volatility and zero. The unconditional long run variance is used to initialize the seasonality volatility process. All estimations are performed in MATLAB. Three cases are needed to determine an improvement or to exclude seasonality components or asymmetry in volatility.

- Case I

Constraints are imposed on an asymmetric parameter to become zero, a move which leads to the GARCH process in seasonal volatility. If the likelihood ratio test cannot reject zero, the hypothesis is a restricted model. This indicates that the GARCH process is better than the GJR-GARCH process.

$$\alpha_2 = 0$$

- Case II

The weekly and yearly seasonality parameters in a volatility model are assumed to be zero. The assumption of zero allows us to examine whether or not there is a benefit to involving seasonality in the volatility model.

$$\gamma_{vwk}, \varphi_{vwk}, \gamma_{vyk}, \varphi_{vyk} = 0$$

- Case III

The final case investigates the effects of weekly and yearly seasonality in mean equations. All parameters that represent seasonality in mean equations are assumed to be zero.

$$\gamma_{mwk}, \varphi_{mwk}, \gamma_{myk}, \varphi_{myk} = 0$$

#### 4.3.2.4 Value-at-Risk

Value-at-Risk (VaR) is a standard financial risk management tool employed by many investment firms and financial institutions to evaluate potential losses over a certain period with a given probability. The key component losses of VaR is a standard deviation; many forecasters attempt to improve their prediction performances by estimating the standard deviation with various approaches, such as historical volatility and fat-tailed distribution calibrations. The application of our seasonal volatility model in VaR is demonstrated by estimating VaR for the one-day and 5-day horizons. By simply multiplying a standard deviation with the confidence level we discern VaR. The one-day VaR is calculated as

$$VaR_t = -\sigma_t \times \Phi_p^{-1} \tag{4.14}$$

However, multi-period VaR of time vary volatility over the next K days is estimated as

$$VaR_{t,t+K} = -\sigma_{t,t+K} \times \Phi_p^{-1}$$

where

$$\sigma^2_{t+1,t+K} = K\sigma^2 + \sum_{k=1}^{K} \left(\beta + \alpha_1 + \frac{1}{2}\alpha_2\right)^{k-1} \left(\sigma^2_{t+1} - \sigma^2\right) \tag{4.15}$$

#### 4.3.2.5 Backtesting

**Failure test**

Our approach for verifying the accuracy of the value-at-risk (VaR) model uses the failure test. A failure occurrence indicates the actual loss that exceeds the VaR estimation. The hypothesis for the failure test is

$$H_0 : p = 1 - c$$

$$H_a : p \neq 1 - c$$

where $c$ is the given confidence level of VaR, and $p$ is the expected failure rate. The number of failure occurences follow the binomial probability distribution as

$$f(x) = \begin{pmatrix} T \\ x \end{pmatrix} p^x (1-p)^{T-x} \tag{4.16}$$

where $T$ is the total observations, $x$ is the number of failed occurrences under a null hypothesis, the $c$ % VaR model is accurate and a return falls in the tail with a probability of $p$ %. A fall in the target probability will result in a Bernoulli trial if null is accepted (Jorison, 2007).

**Independence Test**

The dynamic quantile (DQ) test, initially composed by Engle and Manganelli (2004) is another backtesting method for VaR. Engle and Manganelli presented a new approach to evaluate goodness-of-fit of quantile VaR, which is called conditional autoregressive value-at-

risk (CAViaR). As we know that the good VaR estimations should generate the probability of excess the estimations are equivalent to a confidence level $\Pr\left[y_t < VaR_{t|t-1}(\theta)\right] = \theta.$, which is determined by testing an indicator function. The indicator function is $I = \left(y_t < VaR_{t|t-1}(\theta)\right)$ that must be an i.i.d if the VaR computation is correct.

Fortunately, they demonstrate the hit function in the DQ test approach and allow the inclusion of other variable lags. This method is their important contribution because it allows evaluating the performance of different types of VaR methods, not only CAViaR. The hit function is a binary result comparing the estimated VaR and the actual return. It can be scaled as

$$Hit_t \equiv I\left(y_t < f_t\left(\beta^0\right)\right) - \theta = \begin{cases} 1-\theta & \textit{with probability } \theta \\ -\theta & \textit{with probability } (1-\theta) \end{cases}$$

The requisites of realisable VaR are that the $Hit$ variable has both zero unconditional and conditional expectations. These mean that there is no correlation between $Hit_t$ and a set of variables including lagged hit and VaR. A linear regression of these condition assessments is written as

$$Hit_t = \alpha_0 + \sum_{i=1}^{M} \alpha_i Hit_{t-i} + \sum_{j=0}^{N} \alpha_{M+j} VaR_{t-j} + \varepsilon_t \tag{4.17}$$

In this test, the linear regression includes a constant, four lagged hit and VaR. The statistic DQ dynamic quantile test is

$$DQ = \frac{\hat{w}' X' X \hat{w}}{\theta(1-\theta)}$$

where

$$\hat{w} = \begin{bmatrix} 1 & \alpha_1 & \cdots & \alpha_{M+j} \end{bmatrix}'$$

and

$$X = \begin{bmatrix} \alpha_0 & Hit_{t-1} & \cdots & Hit_{t-M} & VaR_{t-1} & \cdots & VaR_{t-N} \end{bmatrix}$$

The null hypothesis of a DQ test is no autocorrelation in the hit function and is uncorrelated with the VaR. P-value is calculated to determine whether the null hypothesis is either accepted or rejected the null hypothesis. In this calculation, the focus is on a two-sided test at 10% significance level. Thus, if the p value higher than 0.05, the null hypothesis will be accepted. Moreover, the DQ is asymptotically $\lambda^2$ distributed with $(M + N + 1)$ degrees of freedom, therefore the null hypothesis will be accepted if the DQ statistic lower than the critical value of $\lambda^2$ distribution. The realised VaR model should provide independent forecasts, as used, for example, in Taylor (2008).

## 4.4 Empirical Results

### 4.4.1 GARCH and GJR-GARCH Estimations

The GARCH and the GJR-GARCH models' parameters of all three agricultural commodities tested in this thesis are presented in Table 4.2. For example, the drift term of GARCH with Gaussian of rubber is 0.000008. The value of the parameter $\beta$ is 0.90, which indicating that the time varying volatility has a long memory for futures rubber returns. Moreover, the sum of $\alpha_1$ and $\beta$ is 0.98159, which implies a volatility half-life of about 37 days. The loglikelihood is 12590.52. The asymmetric parameter is $\alpha_2$ in GJR-GARCH and in Gaussian, 0.008115. The likelihood is 12590.88. The likelihood (LR) test is the statistical test used to compare two models which have different numbers of parameters. It indicates the better fit model. The LR test between GARCH and GJR-GARCH with Gaussian is 0.6988, which is lower than the critical value. This means there is no evidence that it is beneficial to include the asymmetric effect in the volatility model. The LR tests for Standardised-t and GED are 0.1676 and 0.7054, therefore the GARCH is also an optimal volatility models for rubber. The estimations with the GED error distribution model are superior.

Tables 4.3 and 4.4 report the calibrations of white sugar and rough rice using GARCH and GJR-GARCH. For sugar, GED outperforms, and the asymmetric effect is suitable to be added in the volatility model according to the LR test. For example, the LR tests are 23.5077, 32.2520, and 15.3376 for Gaussian, Standardised-t and GED respectively, which are

higher than the critical value. These indicate that the GJR-GARCH is suitable to use for a volatility model for sugar. In addition, negative asymmetric coefficients have been estimated in all distributions. These findings contradict the stock markets, which normally increase the volatility when there is a price fall. The GARCH is optimal for rough rice according to the LR test, which is similar to rubber; however, the Standardised-t error distribution seems to provide a higher calibration performance than the other distributions. These results are used as the standard volatility process before seasonal parameters are included, as shown in equation 4.13.

### 4.4.2 Seasonal Volatility Estimations

This section will explain the seasonality volatility estimations in equation 4.13. For each commodity, two data sets are estimated. First, we estimated the model, using data from beginning to the end of 2010, and then we estimated the model by including 2011 data. The two data sets are designed to evaluate the forecasting accuracy.

The likelihood results from all calibrations are displayed in Table 4.5. The model is re-estimated several times with constraints on the parameters to test the significance of asymmetric and seasonal effects as explained in section 4.3.2.3. The LR test was used because, with these possibly over-parameterised models, the calibrations of standard errors are unreliable. The LR test statistics are represented in Table 4.6.

In Case I model, only the asymmetrical parameter is constrained, and the comparison is based on an LR test with one degree of freedom. The estimations indicate that the presence of seasonality in the volatility and mean models show a significant asymmetrical effect for white sugar alone of the three agricultural commodities tested in this chapter. The LR test for white sugar is 23.12; it is higher than the critical value at 3.84. Therefore, the restricted model is rejected. However, the asymmetrical effect on volatility parameters is insignificant for rubber and rough rice; thus, the GARCH process outperforms. The results are similar to those of the GARCH and GJR-GARCH estimations in the last section.

Table 4.2: GARCH and GJR-GARCH estimations for rubber

**GARCH**

| Rubber | Gaussian | | Standardised-t | | GED | |
|---|---|---|---|---|---|---|
| | **Coefficient** | **S.E.** | **Coefficient** | **S.E** | **Coefficient** | **S.E** |
| $\omega$ | 0.000008 | 0.000001 | 0.000007 | 0.000001 | 0.000007 | 0.000001 |
| $\alpha_1$ | 0.079534 | 0.003727 | 0.090649 | 0.004935 | 0.088728 | 0.005277 |
| $\beta$ | 0.902058 | 0.004284 | 0.899033 | 0.005307 | 0.899752 | 0.006292 |
| $\mu$ | 0.000404 | 0.000127 | 0.000429 | 0.000278 | 0.000071 | 0.005375 |
| $\nu$ | | | 6.472670 | 0.311363 | 1.187017 | 0.019787 |
| **Loglikelihood** | 12590.5297 | | 12668.2300 | | 12717.6803 | |
| **LR (Distibution)** | | | 155.4006 | | 254.3012 | |

**GJR-GARCH**

| Rubber | Gaussian | | Standardised-t | | GED | |
|---|---|---|---|---|---|---|
| | **Coefficient** | **S.E** | **Coefficient** | **S.E** | **Coefficient** | **S.E** |
| $\omega$ | 0.000008 | 0.000001 | 0.000007 | 0.000001 | 0.000007 | 0.000001 |
| $\alpha_1$ | 0.076129 | 0.003919 | 0.088228 | 0.005833 | 0.084366 | 0.005635 |
| $\beta$ | 0.901500 | 0.004795 | 0.898443 | 0.005496 | 0.898445 | 0.006007 |
| $\mu$ | 0.000366 | 0.000130 | 0.000413 | 0.000122 | 0.000057 | 0.000084 |
| $\nu$ | - | - | 6.485971 | 0.335087 | 1.185786 | 0.021805 |
| $\alpha_2$ | 0.008115 | 0.005279 | 0.005383 | 0.006857 | 0.010760 | 0.007156 |
| **Loglikelihood** | 12590.8791 | | 12668.3138 | | 12718.0330 | |
| **LR (Distibution)** | | | 154.8694 | | 254.3078 | |
| **LR (GARCH and GJR)** | 0.6988 | | 0.1676 | | 0.7054 | |

Table 4.3: GARCH and GJR-GARCH estimations for white sugar

**GARCH**

| White Sugar | Gaussian | | Standardised-t | | GED | |
|---|---|---|---|---|---|---|
| | **Coefficient** | **S.E.** | **Coefficient** | **S.E** | **Coefficient** | **S.E** |
| $\omega$ | 0.000028 | 0.000004 | 0.000006 | 0.000618 | 0.000012 | 0.000003 |
| $\alpha_1$ | 0.217104 | 0.038544 | 0.080331 | 4.482126 | 0.136849 | 0.018502 |
| $\beta$ | 0.703703 | 0.047444 | 0.909669 | 6.051653 | 0.832239 | 0.024846 |
| $\mu$ | -0.000139 | 0.009689 | 0.000053 | 0.015154 | 0.000000 | 0.000000 |
| $\nu$ | | | 3.263375 | 2.760656 | 0.897530 | 0.011512 |
| **Loglikelihood** | 10145.0592 | | 10495.5098 | | 10522.3356 | |
| **LR (Distibution)** | | | 700.9012 | | 754.5528 | |

**GJR-GARCH**

| White Sugar | Gaussian | | Standardised-t | | GED | |
|---|---|---|---|---|---|---|
| | **Coefficient** | **S.E.** | **Coefficient** | **S.E** | **Coefficient** | |
| $\omega$ | 0.000027 | 0.000004 | 0.000001 | 0.000000 | 0.000001 | 0.000000 |
| $\alpha_1$ | 0.270327 | 0.021412 | 0.049088 | 0.005265 | 0.054134 | 0.006699 |
| $\beta$ | 0.716227 | 0.029839 | 0.971378 | 0.003340 | 0.964733 | 0.005271 |
| $\mu$ | 0.000177 | 0.002345 | -0.000002 | 0.000093 | 0.000000 | 0.000000 |
| $\nu$ | - | - | 3.334781 | 0.000338 | 0.902971 | 0.010808 |
| $\alpha_2$ | -0.125941 | 0.022135 | -0.040953 | 0.004743 | -0.043221 | 0.005897 |
| **Loglikelihood** | 10156.813067 | | 10511.6358 | | 10530.0044 | |
| **LR (Distibution)** | | | 709.6455 | | 746.3827 | |
| **LR (GARCH and GJR)** | 23.5077 | | 32.2520 | | 15.3376 | |

Table 4.4: GARCH and GJR-GARCH estimations for rough rice

**GARCH**

| Rough Rice | Gaussian | | Standardised-t | | GED | |
|---|---|---|---|---|---|---|
| | **Coefficient** | **S.E.** | **Coefficient** | **S.E** | **Coefficient** | **S.E** |
| $\omega$ | 0.000053 | 0.000006 | 0.000005 | 0.000008 | 0.000030 | 0.000007 |
| $\alpha_1$ | 0.150167 | 0.011997 | 0.052063 | 0.062226 | 0.116192 | 0.015089 |
| $\beta$ | 0.695889 | 0.025695 | 0.939176 | 0.078455 | 0.796222 | 0.031403 |
| $\mu$ | 0.000880 | 0.000173 | 0.000026 | 0.059327 | 0.001929 | 0.000630 |
| $\nu$ | | | 4.007585 | 0.604180 | 1.180676 | 0.019115 |
| **Loglikelihood** | 6162.2908 | | 6293.1343 | | 6291.8884 | |
| **LR (Distibution)** | | | 261.6870 | | 259.1952 | |

**GJR-GARCH**

| Rough Rice | Gaussian | | Standardised-t | | GED | |
|---|---|---|---|---|---|---|
| | **Coefficient** | **S.E** | **Coefficient** | **S.E** | **Coefficient** | **S.E** |
| $\omega$ | 0.000051 | 0.000006 | 0.000005 | 0.000002 | 0.000026 | 0.000006 |
| $\alpha_1$ | 0.137961 | 0.011046 | 0.051686 | 0.007820 | 0.096478 | 0.013496 |
| $\beta$ | 0.700500 | 0.022799 | 0.932864 | 0.011850 | 0.811919 | 0.028055 |
| $\mu$ | 0.000831 | 0.000175 | 0.000016 | 0.000192 | 0.000000 | 0.000001 |
| $\nu$ | - | - | 4.020417 | 0.180737 | 1.084444 | 0.021115 |
| $\alpha_2$ | 0.031483 | 0.016280 | 0.010836 | 0.010197 | 0.038962 | 0.017190 |
| **Loglikelihood** | 6162.7970 | | 6293.3114 | | 6292.8276 | |
| **LR (Distibution)** | | | 261.0288 | | 260.0612 | |
| **LR (GARCH and GJR)** | 1.0124 | | 0.3542 | | 1.8784 | |

Moreover, of the asymmetrical parameters shown in Table A.3 white sugar is negative. In contrast, a positive but insignificant asymmetrical effect has been found in rubber and rough rice. This means that volatility decreases when the price of white sugar falls. Therefore, a good agricultural asymmetrical variable represents the positive correlation between volatility and a drop in price, otherwise it is not appropriately involved in the volatility model. Many empirical studies on commodities claim that a negative coefficient is often discovered in commodities, which contrasts with equity markets such as in Huang, et al (2009).

The second constraint, Case II model, is the test of seasonality parameters in the volatility process. For case II model, the seasonality components in the volatility model are constrained to zero. The LR test shows that seasonality in volatility model is insignificant for rubber and white sugar but significant for rough rice. For example, the LR test of rubber is 6.13, which is lower than the 12.59 of the critical value. Hence, the restricted model is accepted. This means that including seasonal parameters in the volatility process is not necessary for this model. Lastly, we tested the benefit of incorporating seasonal parameters in mean returns of a seasonal volatility process using called Case III model. For all three commodities, seasonal components in mean returns should be included as all restricted models are rejected.

Table 4.7 exhibits optimal seasonal factors and error distributions for each agricultural commodity. The estimation initially assumes three different error distributions for the referenced model. The LR test indicates that GED is an optimal error distribution model for rubber and white sugar. The maximum likelihood of rough rice is found through estimations using the Standardised-t model. The optimal volatility model for rubber is the GARCH process with seasonality in the mean equation. The GJR-GARCH with seasonality in the mean equation is an optimal volatility model for white sugar. Finally, the optimal rough rice seasonal volatility model is the GARCH with seasonality in the mean and volatility equation. Table 4.8 and 4.9 illustrate the estimated parameters of optimal seasonal volatility of both data sets. Moreover, the estimations of other error distribution are represented in Tables A.1 to A.6.

Table 4.5: Likelihood of different constraints on asymmetric effect and seasonality components

| | Referenced Model | Case I Model | Case II Model | Case III Model |
|---|---|---|---|---|
| **Rubber** | | | | |
| **No. of calibrating parameters** | 20 | 19 | 14 | 12 |
| **Gaussian** | 12615.06 | 12614.60 | 12612.00 | 12595.59* |
| **Standardised-t** | 12689.83 | 12688.89 | 12687.91 | 12668.43* |
| **GED** | 12729.93 | 12729.27 | 12727.93 | 12718.96* |
| **White Sugar** | | | | |
| **No. of calibrating parameters** | 18 | 17 | 12 | 12 |
| **Gaussian** | 10184.09 | 10172.53* | 10169.21* | 10171.21* |
| **Standardised-t** | 10532.78 | 10515.47* | 10528.39 | 10516.18* |
| **GED** | 10539.38 | 10532.57* | 10534.27 | 10525.32* |
| **Rough Rice** | | | | |
| **No. of calibrating parameters** | 22 | 21 | 14 | 14 |
| **Gaussian** | 6229.42 | 6227.81 | 6167.36* | 6221.75* |
| **Standardised-t** | 6324.43 | 6324.38 | 6299.37* | 6302.16* |
| **GED** | 6323.14 | 6321.86 | 6295.55* | 6315.02* |

* = the restricted model is rejected.

Table 4.6: Likelihood ratio test statistics of different constraints on asymmetric effect and seasonality components

| | Referenced Model | Case I Model | Case II Model | Case III Model |
|---|---|---|---|---|
| **Rubber** | | | | |
| **No. of calibrating parameters** | 20 | 19 | 14 | 12 |
| **Gaussian** | - | 0.92 | 6.12 | 38.94* |
| **Student-t** | - | 1.88 | 3.84 | 42.80* |
| **GED** | - | 1.32 | 4.00 | 21.94* |
| **White Sugar** | | | | |
| **No. of calibrating parameters** | 18 | 17 | 12 | 12 |
| **Gaussian** | - | 23.12* | 29.76* | 25.76* |
| **Student-t** | - | 34.62* | 8.78 | 33.20* |
| **GED** | - | 13.62* | 10.22 | 28.12* |
| **Rough Rice** | | | | |
| **No. of calibrating parameters** | 22 | 21 | 14 | 14 |
| **Gaussian** | - | 3.22 | 124.12* | 15.34* |
| **Student-t** | - | 0.10 | 50.12* | 44.54* |
| **GED** | - | 2.56 | 55.18* | 16.24* |

* = the restricted model is rejected.

## Value-at-Risk

The implications of seasonal volatility on one-day and 5-day value-at-risk (VaR) are illustrated. The optimal seasonal-GARCH volatility models and the GARCH model used in this VaR estimation achieve 90, 95, 99 and 99.5 % confidence levels with optimal error distributions as shown between Tables 4.10 and 4.12. The performance comparisons between both volatility processes point out a superior model. However, only the appropriate seasonal volatility model and the error distribution model identified are explained in this section, VaR estimations with other error distributions are presented between Tables A.7 and A.12. Two backtestings, consisting of a failure test and a dynamic quantile, evaluate the goodness of fit. Only out-of-sample tests are explained.

A benefit of seasonal-GARCH that has already been incorporated into the yearly seasonal component is that the calibration of volatility parameters is required once per year. Hence, there is no need for the daily re-calibration of the volatility model, which is an advantage within our proposed volatility model. However, the VaR estimation is calculated on a daily basis because the current seasonal-GARCH volatility process consists of the past volatility process and the noise term.

Figures 4.1 and 4.2 compare one-day and 5-days VaR at a 99% confidence level with the actual return over the period of 2010 and 2011. Less volatility in VaR has been found when computing VaR with seasonal-GARCH. For instance, the VaR of GARCH and seasonal-GARCH and the actual return are depicted in Figure 4.1. The left column represents the VaR of GARCH with Gaussian, and the right column is the VaR of the optimal seasonal-GARCH with suitable error distributions. These clearly demonstrate less volatility in VaR of seasonal-GARCH than the GARCH process. These are advantages of the seasonal-GARCH process in

Table 4.7: Summary of existence asymmetry and seasonal component of seasonal volatility model

| | Optimal Distribution | Asymmetry | Seasonality in Volatility | Seasonality in Mean |
|---|---|---|---|---|
| Rubber | GED | | | ⁄ |
| White Sugar | GED | ⁄ | | ⁄ |
| Rough Rice | Standardised-t | | ⁄ | ⁄ |

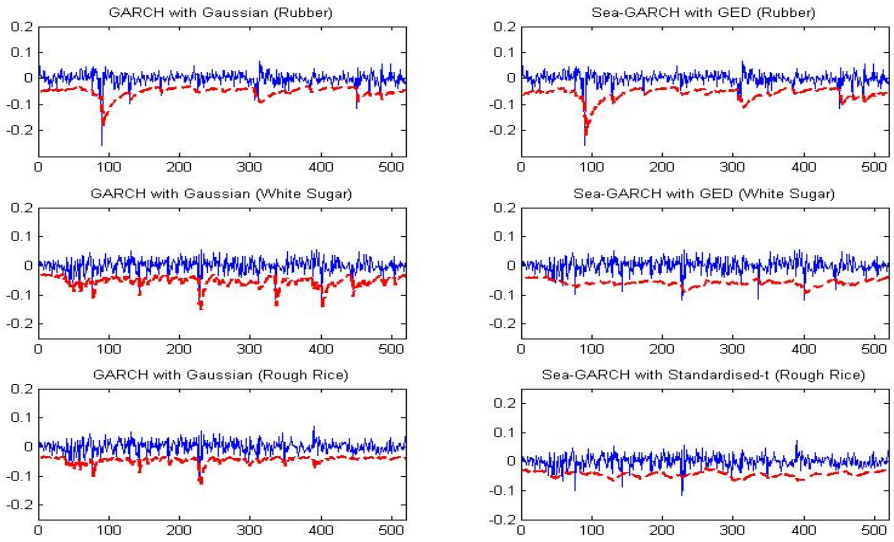
Table 4.8: First seasonal volatility estimations for all agricultural commodities

| | **Rubber** | | **White Sugar** | | | **Rough Rice** | |
|---|---|---|---|---|---|---|---|
| | **GED** | | **GED** | | | **Standardised-t** | |
| | **Coefficient** | **S.E** | **Coefficient** | **S.E** | | **Coefficient** | **S.E** |
| $\omega$ | 0.000007 | 0.619201 | 0.000001 | 0.045973 | $\omega$ | 0.000001 | 0.000006 |
| $\alpha_1$ | 0.088381 | 0.025926 | 0.050804 | 0.000336 | $\alpha$ | 0.055959 | 0.030084 |
| $\beta$ | 0.898837 | 0.178657 | 0.967948 | 0.000103 | $\beta$ | 0.916547 | 0.072792 |
| $\mu$ | 0.000297 | 0.070114 | -0.000009 | 0.006307 | $\mu$ | -0.000056 | 0.000307 |
| $\nu$ | 1.231145 | 0.037796 | 0.931931 | 0.000635 | $\nu$ | 4.510316 | 0.097855 |
| $\alpha_2$ | - | | -0.042379 | 0.000768 | $\alpha_2$ | - | |
| $\gamma_{mw1}$ | 0.000379 | 0.148062 | 0.000478 | 0.009377 | $\gamma_{mw1}$ | 0.000769 | 0.000326 |
| $\varphi_{mw1}$ | -0.000071 | 0.279620 | -0.000027 | 0.010442 | $\varphi_{mw1}$ | -0.000699 | 0.000173 |
| $\gamma_{mw2}$ | -0.000289 | 0.199883 | 0.000203 | 0.008352 | $\gamma_{mw2}$ | 0.000259 | 0.000308 |
| $\varphi_{mw2}$ | -0.000321 | 0.200860 | -0.000011 | 0.029660 | $\varphi_{mw2}$ | 0.000746 | 0.000308 |
| $\gamma_{my1}$ | 0.000256 | 0.215825 | -0.000245 | 0.025150 | $\gamma_{my1}$ | 0.000590 | 0.000375 |
| $\varphi_{my1}$ | 0.000476 | 0.589347 | 0.000133 | 0.011825 | $\varphi_{my1}$ | 0.000105 | 0.000205 |
| $\gamma_{my2}$ | -0.000094 | 0.171344 | 0.000538 | 0.006371 | $\gamma_{vw1}$ | -0.000003 | 0.000016 |
| $\varphi_{my2}$ | -0.000177 | 0.287462 | -0.000402 | 0.003781 | $\varphi_{vw1}$ | 0.000006 | 0.000003 |
| $\gamma_{my3}$ | 0.000179 | 0.330773 | | | $\gamma_{vw2}$ | -0.000003 | 0.000005 |
| $\varphi_{my3}$ | 0.000779 | 0.397526 | | | $\varphi_{vw2}$ | 0.000001 | 0.000018 |
| $\gamma_{my4}$ | -0.000337 | 0.453413 | | | $\gamma_{vy1}$ | -0.000012 | 0.000022 |
| $\varphi_{my4}$ | 0.000011 | 0.344812 | | | $\varphi_{vy1}$ | 0.000009 | 0.000014 |
| $\gamma_{my5}$ | 0.000398 | 0.248938 | | | $\gamma_{vy2}$ | -0.000006 | 0.000026 |
| $\varphi_{my5}$ | -0.000570 | 0.569787 | | | $\varphi_{vy2}$ | 0.000007 | 0.000008 |
| | | | | | $\gamma_{vy3}$ | -0.000002 | 0.000004 |
| | | | | | $\varphi_{vy3}$ | 0.000012 | 0.000034 |
| | | | | | $\gamma_{vy4}$ | 0.000002 | 0.000018 |
| | | | | | $\varphi_{vy4}$ | 0.000002 | 0.000015 |
| | | | | | $\gamma_{vy5}$ | 0.000014 | 0.000003 |
| | | | | | $\varphi_{vy5}$ | 0.000004 | 0.000008 |
| | | | | | $\gamma_{vy6}$ | 0.000018 | 0.000032 |
| | | | | | $\varphi_{vy6}$ | -0.000014 | 0.000023 |
| Loglikelihood | 12668.4290 | | 10534.2790 | | | 6324.3895 | |
| AIC | -25403.2049 | | -21024.5579 | | | -12592.7789 | |

Table 4.9: Second seasonal volatility estimations for all agricultural commodities

| | **Rubber** | | **White Sugar** | | | **Rough Rice** | |
|---|---|---|---|---|---|---|---|
| | **GED** | | **GED** | | | **Standardised-t** | |
| | **Coefficient** | **S.E** | **Coefficient** | **S.E** | | **Coefficient** | **S.E** |
| $\omega$ | 0.000008 | 0.029501 | 0.000001 | 0.049609 | $\omega$ | 0.000000 | 0.000009 |
| $\alpha_1$ | 0.090548 | 0.052282 | 0.054913 | 0.014055 | $\alpha$ | 0.047985 | 0.006172 |
| $\beta$ | 0.896227 | 0.035125 | 0.964574 | 0.036602 | $\beta$ | 0.928803 | 0.027545 |
| $\mu$ | 0.000352 | 0.104614 | 0.000043 | 0.033549 | $\mu$ | -0.000077 | 0.000136 |
| $\nu$ | 1.179721 | 0.002581 | 0.936897 | 0.023882 | $\nu$ | 4.863816 | 0.003652 |
| $\alpha_2$ | - | | -0.040428 | 0.047543 | $\alpha_2$ | - | |
| $\gamma_{mw1}$ | 0.000375 | 0.190794 | 0.000446 | 0.062036 | $\gamma_{mw1}$ | 0.000982 | 0.000205 |
| $\varphi_{mw1}$ | -0.000032 | 0.040818 | -0.000022 | 0.044438 | $\varphi_{mw1}$ | -0.000559 | 0.000177 |
| $\gamma_{mw2}$ | -0.000257 | 0.154326 | 0.000173 | 0.050682 | $\gamma_{mw2}$ | 0.000260 | 0.000194 |
| $\varphi_{mw2}$ | -0.000335 | 0.037063 | -0.000005 | 0.030896 | $\varphi_{mw2}$ | 0.000641 | 0.000191 |
| $\gamma_{my1}$ | 0.000289 | 0.441845 | -0.000253 | 0.059968 | $\gamma_{my1}$ | 0.000465 | 0.000181 |
| $\varphi_{my1}$ | 0.000411 | 0.204971 | 0.000064 | 0.024613 | $\varphi_{my1}$ | -0.000267 | 0.000200 |
| $\gamma_{my2}$ | -0.000107 | 0.152827 | 0.000472 | 0.030456 | $\gamma_{vw1}$ | -0.000006 | 0.000001 |
| $\varphi_{my2}$ | -0.000197 | 0.061023 | -0.000438 | 0.048081 | $\varphi_{vw1}$ | 0.000006 | 0.000001 |
| $\gamma_{my3}$ | 0.000146 | 0.133891 | | | $\gamma_{vw2}$ | -0.000001 | 0.000001 |
| $\varphi_{my3}$ | 0.000657 | 0.195370 | | | $\varphi_{vw2}$ | -0.000002 | 0.000001 |
| $\gamma_{my4}$ | -0.000351 | 0.321964 | | | $\gamma_{vy1}$ | -0.000009 | 0.000001 |
| $\varphi_{my4}$ | -0.000053 | 0.059837 | | | $\varphi_{vy1}$ | 0.000007 | 0.000001 |
| $\gamma_{my5}$ | 0.000416 | 0.313412 | | | $\gamma_{vy2}$ | -0.000003 | 0.000002 |
| $\varphi_{my5}$ | -0.000579 | 0.132526 | | | $\varphi_{vy2}$ | 0.000005 | 0.000002 |
| | | | | | $\gamma_{vy3}$ | -0.000001 | 0.000001 |
| | | | | | $\varphi_{vy3}$ | 0.000011 | 0.000001 |
| | | | | | $\gamma_{vy4}$ | 0.000001 | 0.000001 |
| | | | | | $\varphi_{vy4}$ | 0.000001 | 0.000002 |
| | | | | | $\gamma_{vy5}$ | 0.000011 | 0.000001 |
| | | | | | $\varphi_{vy5}$ | 0.000002 | 0.000001 |
| | | | | | $\gamma_{vy6}$ | 0.000015 | 0.000002 |
| | | | | | $\varphi_{vy6}$ | -0.000012 | 0.000001 |
| Loglikelihood | 13365.6452 | | 11129.7610 | | | 7017.3241 | |
| AIC | -26696.4867 | | -22215.5221 | | | -13978.8270 | |

Figure 4.1: Comparison of estimated one-days VaR with GARCH and Seasonal Volatility at 99% confidencel level and the actual return

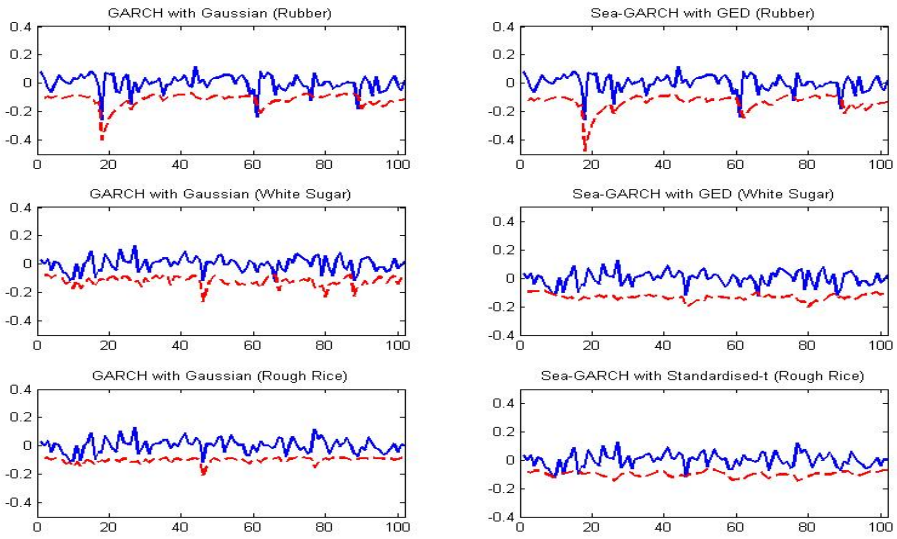



capturing the seasonal movement.

Tables 4.10 to 4.12 show out-of-sample tests over the period of 2011 and 2012 for three agricultural commodities with both GARCH (Gaussian) and optimal seasonal volatility. The DQ test cannot be calculated if there is no evidence of the excess return where the actural returns compare with the VaR estimations. The p-value is provided for both failure and DQ tests and the higher p-value value indicate satisfied VaR confidence levels and iid. Four different confidence levels are also represented, which are more alternative confidence levels than depicted in Figures 4.1 and 4.2. These two backtesting methods are required to verify the good VaR. The results of rough rice in Table 4.12 clearly present that seasonal-GARCH performance was superior to GARCH (Gaussian) in one-day VaR; however, GARCH (Gaussian) performed slightly better in 5-days VaR. The VaR performance of rubber and white sugar are similar in both models. In addition, the probability of the desired criteria of seasonal-GARCH is higher than that of GARCH, which show improvement in VaR forecasting performances.

Tables A.7 to A.9 report the backtesting results for GARCH. These results are significant in that they reveal the benefit of using a fat-tailed error distribution, as there is a higher

Figure 4.2: Comparison of estimated 5-days VaR with GARCH and Seasonal Volatility at 99% confidential level and the actual return




number of fat-tailed VaR that satisfied both failure and DQ tests. Moreover, the fat-tailed error distribution produced more realised VaR when the fat-tailed error distributions apply with high confidence levels, such as 99% or 99.5%. Tables A.10 to A.12 shows both normal and fat-tailed error distribution performances of seasonal-GARCH. Similar to the GARCH process, the fat-tailed error distribution slightly outperforms, especially when it has very high confidence levels. In addition, both of the backtesting results point out that seasonal-GARCH is able to produce a longer realisable period, e.g. 5-days VaR rather than a one-day VaR. Hence, the relatively better forecasting performances of VaR with the seasonal-GARCH model are probably caused by the seasonal parameters and the fat-tailed error distribution.

Table 4.10: The out-of-sample backtesting results of rubber VaR estimation with GARCH and Seasonal-GARCH

| Rubber | | GARCH (Gaussian) | | | | Seasonal-GARCH (GED) | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | **90%** | **95%** | **99%** | **99.50%** | **90%** | **95%** | **99%** | **99.50%** |
| **one-day VaR** | **No. of Hit** | 49 | 28 | 16 | 11 | 52 | 27 | 10 | 7 |
| | **Hit Percentage** | 9.42% | 5.38% | 3.08% | 2.12% | 10.00% | 5.19% | 1.92% | 1.35% |
| | **Failure test** | 0.3638 | 0.7004 | 1.0000 | 1.0000 | 0.5368 | 0.6290 | 0.9828 | 0.9948 |
| | **P Value** | 0.3638 | 0.2996 | 0.0000 | 0.0000 | 0.4632 | 0.3710 | 0.0172 | 0.0052 |
| | **DQ** | 24.3553 | 25.3250 | 45.5039 | 41.2995 | 22.0112 | 25.7491 | 12.6701 | 13.3204 |
| | **P Value** | 0.0004 | 0.0003 | 0.0000 | 0.0000 | 0.0012 | 0.0002 | 0.0486 | 0.0382 |
| **5-Day VaR** | **No. of Hit** | 13 | 5 | 3 | 3 | 11 | 6 | 3 | 3 |
| | **Hit Percentage** | 12.75% | 4.90% | 2.94% | 2.94% | 10.00% | 5.58% | 2.12% | 1.54% |
| | **Failure test** | 0.8610 | 0.5980 | 0.9804 | 0.9982 | 0.6789 | 0.7509 | 0.9804 | 0.9982 |
| | **P Value** | 0.1390 | 0.4020 | 0.0196 | 0.0018 | 0.3211 | 0.2491 | 0.0196 | 0.0018 |
| | **DQ** | 12.7207 | 4.4717 | 5.1251 | 16.7160 | 18.5309 | 3.4469 | 5.3040 | 15.0694 |
| | **P Value** | 0.0477 | 0.6131 | 0.5279 | 0.0104 | 0.0050 | 0.7510 | 0.5055 | 0.0197 |

Table 4.11: The out-of-sample backtesting results of sugar VaR estimation with GARCH and Seasonal-GARCH

| Sugar | | GARCH (Gaussian) | | | | Seasonal-GARCH (GED) | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | **90%** | **95%** | **99%** | **99.50%** | **90%** | **95%** | **99%** | **99.50%** |
| **one-day VaR** | **No. of Hit** | 64 | 42 | 13 | 8 | 67 | 38 | 13 | 10 |
| | **Hit Percentage** | 12.31% | 8.08% | 2.50% | 1.54% | 12.88% | 7.31% | 2.50% | 1.92% |
| | **Failure test** | 0.9630 | 0.9990 | 0.9991 | 0.9986 | 0.9859 | 0.9914 | 0.9991 | 0.9999 |
| | **P Value** | 0.0370 | 0.0010 | 0.0009 | 0.0014 | 0.0141 | 0.0086 | 0.0009 | 0.0001 |
| | **DQ** | 79.6454 | 31.0110 | 47.7535 | 17.1729 | 19.0533 | 42.3398 | 23.3756 | 16.0750 |
| | **P Value** | 0.0000 | 0.0000 | 0.0000 | 0.0087 | 0.0041 | 0.0000 | 0.0007 | 0.0134 |
| **5-Day VaR** | **No. of Hit** | 16 | 4 | 1 | 1 | 18 | 8 | 1 | 1 |
| | **Hit Percentage** | 15.69% | 3.92% | 0.98% | 0.98% | 17.65% | 7.84% | 0.98% | 0.98% |
| | **Failure test** | 0.9754 | 0.4183 | 0.7284 | 0.9071 | 0.9943 | 0.9303 | 0.7284 | 0.9071 |
| | **P Value** | 0.0246 | 0.4183 | 0.2716 | 0.0929 | 0.0057 | 0.0697 | 0.2716 | 0.0929 |
| | **DQ** | 11.4719 | 4.5699 | 2.0949 | 3.6619 | 20.0586 | 15.8806 | 3.4383 | 7.4058 |
| | **P Value** | 0.0748 | 0.6000 | 0.9108 | 0.7223 | 0.0027 | 0.0144 | 0.7522 | 0.2849 |

Table 4.12: The out-of-sample backtesting results of rough rice VaR estimation with GARCH and Seasonal-GARCH

| Rough Rice | | GARCH (Gaussian) | | | | Seasonal-GARCH (Standardised-t) | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | 90% | 95% | 99% | 99.50% | 90% | 95% | 99% | 99.50% |
| one-day VaR | No. of Hit | 56 | 36 | 10 | 4 | 59 | 30 | 3 | 0 |
| | Hit Percentage | 10.77% | 6.92% | 1.92% | 0.77% | 11.35% | 5.77% | 0.58% | 0.00% |
| | Failure test | 0.7482 | 0.9786 | 0.9828 | 0.8779 | 0.8629 | 0.8191 | 0.2366 | 0.0738 |
| | P Value | 0.2518 | 0.0214 | 0.0172 | 0.1221 | 0.1371 | 0.1809 | 0.2366 | 0.0738 |
| | DQ | 4.6443 | 7.2769 | 41.2667 | 17.5186 | 6.8455 | 11.0529 | 7.0272 | N/A |
| | P Value | 0.5902 | 0.2960 | 0.0000 | 0.0076 | 0.3354 | 0.0868 | 0.3183 | N/A |
| 5-Day VaR | No. of Hit (5-Day VaR) | 13 | 4 | 0 | 0 | 19 | 9 | 0 | 0 |
| | Hit Percentage | 12.75% | 3.92% | 0.00% | 0.00% | 18.63% | 8.82% | 0.00% | 0.00% |
| | Failure test | 0.8610 | 0.4183 | 0.3587 | 0.5997 | 0.9975 | 0.9682 | 0.3587 | 0.5997 |
| | P Value | 0.1390 | 0.4183 | 0.3587 | 0.4003 | 0.0025 | 0.0318 | 0.3587 | 0.4003 |
| | DQ | 18.4796 | 9.2863 | N/A | N/A | 17.1865 | 17.7160 | N/A | N/A |
| | P Value | 0.0051 | 0.1581 | N/A | N/A | 0.0086 | 0.0070 | N/A | N/A |

## 4.5 Conclusion

This chapter aims to propose a return volatility model for agricultural commodities. The asymmetric effect and different patterns of seasonality in mean return and volatility have been detected. The results indicate that the inclusion of seasonality is vital in providing more realistic volatility models; however, the asymmetric effect is different across the samples. Only a negative asymmetric variable is suitable for incorporation into the volatility model.

VaR is used to determine the volatility process in out-of-sample tests. Comparisons between the GARCH (Gaussian) and the optimal proposed seasonal-GARCH forecasting performances are demonstrated to verify the effective volatility model by failure test and independence test. The empirical results show that the proposed model, such as the volatility model with seasonality in mean and the volatility model with seasonality in mean and volatility are better than the GARCH (Gaussian) for computing VaR. Furthermore, the fat-tailed distribution model is better than the Gaussian distribution, for example, the GED distribution is suitable for rubber and white sugar, and the Standardised-t distributions should be employed with rough rice for improving forecasting performances. Further research on the applications of this seasonal volatility model in other aspects, such as portfolio choice and asset pricing, would be beneficial.

# Chapter 5

# Modelling Convenience Yield for Agricultural Commodities

## 5.1 Introduction

Convenience yield is a benefit to the physical holder of a commodity as defined by Working (1948,1949) and Kaldor (1939). A decrease in supply increases the benefit to the physical holder as shown by the convenience yield. The frequent uncertainty of agricultural supply in the world market due to factors such as weather and political instability makes convenience yield a crucial element in the futures price formula.

In the last decade, there have been many studies that show how to estimate the convenience yield of different commodities, such as crude oil and metal; however, there are few studies on agriculture and convenience yield. Hence, this chapter aims to explain convenience yield behaviour and model the convenience yield of agricultural commodities. In addition, we will investigate the exchange rate's effects on convenience yield.

Firstly, this chapter examines the convenience yield behaviour of agricultural commodities that are traded in the recognized international futures exchange markets. Seven agricultural futures contract prices, namely, rubber, rough rice, white sugar, raw sugar, cotton, corn and coffee are examined. These futures contracts are traded in the world leading futures exchange markets, the Tokyo Commodity Exchange (TOCOM), Chicago Board of Trade (CBOT), New York Board of Trade (NYBOT), and LIFFE, London. These markets are referenced by ex-

porters for the international agricultural prices on specific agricultural commodities.

We estimate the net convenience yield by using the backwardation approach and perform investigations of heteroskedasticity for all agricultural commodities. There are five heteroskedasticity tests: the Breusch-Pagan test (BP), Glejser test, Harvey test, ARCH test, and our proposed heteroskedasticity test. Moreover, the AR(1) process is used in the modelling by assuming GARCH and IGARCH with Gaussian and Standardised-t error distribution. In the final study, we focus on the effects of the exchange rate on the net convenience yield, especially for rubber, white sugar and white sugar.

This chapter is organized as follows: first, literature on convenience yield modelling and then the effects of exchange rate will be discussed. Section 5.3, data and methodology are provided. Then in section 5.4, the empirical resulttis of convenience yield modelling and the tests of our exchange rate effect hypothesis are shown. Finally, we reach some conclusions and discuss our contributions.

## 5.2 Literature Review

### 5.2.1 Convenience Yield Modelling

Convenience yield is the benefit to a physical asset holder that is not available in a futures contract. Convenience yield is an economically significant concept that explains the relationship between the spot price and futures price of the assets. In regards to the theory of storage, Kaldor (1939) and Working (1948,1949) explain the inverted market phenomenon, in which spot prices are higher than futures prices due to convenience yield. The cost-of-carry provides the fair price of futures contracts, as expressed below

$$F_{t,T} = S_0 \exp^{(r+c-cy)(T-t)} \tag{5.1}$$

where $F_{t;T}$ is a future contract price, $S_0$ is a spot price,$r$ is a risk free rate, $c$ is a storage

cost, $cy$ is a convenience yield, $T$ is time at the maturity, and $T-t$ is days to maturity. Black (1976) contributes the cost-of-carry formula. Three possibilities of asset price are assumed as the value of a forward contract, a future contract and an option contract in the content of the captital asset pricing formula. The change between the spot price and futures price is considered, the benefit of holding commodity rather than the contract is mentioned. Gibson and Schwartz (1990) claim that the relationship between futures prices and spot prices of many commodities is explained by convenience yield.

The constant variables are assumed in the beginning of convenience invention. Heaney (2002) constructs the convenience yield model which requires only three variables, namely, underlying asset price volatility, futures contract price volatility and time to maturity, and employs the maximum trading strategy concept (Longstaff, 1995) to evaluate the convenience yield for copper, lead and zinc. The simple trading strategy is used to simulate a transaction of futures trading, so the approximation of convenience yield can be written as

$$CY_{t,T} = V_{t,T}(S_{it}, T) - V_{t,T}(F_{t,T}, T) \tag{5.2}$$

where $V$ is the value trading strategy of a trader who can choose to sell the underlying asset before the futures contract's maturity.

Wei and Zhu (2006) also utilise the basic concept of a trading strategy, by assuming the market is efficient and there are no arbitrage opportunities. There are two time periods in this setting: the investor can buy and hold the asset until a sale at T and take a short position in the futures contract. The total return of this strategy is

$$(P_{t+1} - P_t + CY_{t,T}) + (F_T - P_{t+1}) = F_T - P_t + CY_{t,T} \tag{5.3}$$

where $(P_{t+1} - P_t + CY_t)$ is the holding position during a period and $(F_t - P_{t+1})$ is the gain of a futures contract. If there is no risk in the transaction, and there is a deterministic total return, the investor will gain the return as if they were investing in risk-free asset:

$$rP_t \tag{5.4}$$

Thus, these two alternative investments must be equal:

$$F_t - P_t + CY_{t,T} = rP_t \tag{5.5}$$

Therefore, the net marginal convenience yield is

$$CY_t = (1 + r) P_t - F_t \tag{5.6}$$

Kentsch (2007) forecasts the futures price of crude oil via a convenience yield prediction. The convenience yield process exhibits mean-reverting behaviour, and the approximation can be performed on the autoregressive AR(1) model. The market expectation of convenience yield is determined by the cost-of-carry approach using the following equation,

$$E\left(CY_{t,T}\right) = (1 + r_{t,T}) p_t - f_{t,T} \tag{5.7}$$

under the assumption of a mean-reverting process. The convenience yield is calculated by an autoregressive (AR) model of finite order p which is

$$CY_t = \alpha_0 + \alpha_1 CY_{t-1} + \varepsilon_t \tag{5.8}$$

However, stochastic variables in futures pricing are studied. For example, Fama and French (1987) consider seasonality's effect on variations in convenience yield for several agricultural products. A commodity's futures basis can be described by seasonality. Gibson and Schwartz (1990) develop a model for pricing a futures contract and an option on the futures. They introduce stochastic convenience yield as the second component of the model, adding to the spot price. This is a two-factor model. They also show a negative relationship between inventory levels and convenience yields.

Bjerksund (1991) shows that futures prices and European call options can be modelled by

assuming prices follow a geometric Brownian motion and the convenience yield rate follows an Ornstein-Uhlenbeck process. This research provides useful formulas when evaluating the complex contingent claim and no closed-form formula. Miltersen and Schwartz (1998) and Schwartz (1997) propose a three-factor model to price the commodity price and option by using a stochastic convenience yield and interest rate. This model is constructed using the Heath-Jarrow-Morton (1992) methodology and arbitrage-free assumption for convenience yield and interest rate.

The other approach is to estimate the convenience yield by using the call option framework. This framework suggests the physical commodity holder would have a higher benefit when the commodity price increases but a limited benefit at the agreed price in the futures contract. Thus, these characteristics are the call option features. Heinkel, Howe and Hughes (1990) show theoretically that there are benefits of holding inventory when there is an unexpected demand. Their study framework is based on a two-period setting and assumes that the storage cost and interest rate are zero; hence, the convenience yield is calculated from the difference between the spot price and the futures price. The convenience yield function is integrated over the specified area that represents the increased price during the period of the time to maturity.

Milonas and Thomadakis (1997) propose that annual convenience yields of soybeans, corn, wheat and copper can be modelled by using the call option pricing framework with the assumption of zero storage cost and the underlying asset spot price. The payoff function from the convenience yield at maturity can be written as

$$CY_{t,T} = \max(P_t - F_{t,T}, 0) \tag{5.9}$$

where $P_t$ is the spot price at $T$ and $F_{t,T}$is the futures price. They employ the Fischer (1978) option pricing model to evaluate the convenience yield. They also test four hypotheses: the correlation of convenience yield and inventory level, the effect of spot price volatility on the value of convenience yield, the related convenience yield with time to maturity of the crop cycle, and the study of spot and future price relationship via convenience yield. The results indicate that a negative relationship between inventory level and convenience yield has been

found; moreover, the crop cycle timing also affects the storage level, which leads to a change in convenience yield. In addition, the convenience yield option valuation implies that the variability of the underlying asset price causes a high convenience yield value, which heightens the difference between spot and futures prices.

Lin and Duan (2006) extend the call option model of Milonas and Thomadakis (1997) to value oil convenience yield. They include the storage cost and use the nearest futures contract price as a spot price in their model. The two-period model by Milonas and Thomadakis (1997) is utilised, and the shock effect occurs at t. The payoff functions for the convenience yield are

$$CY_{t,T} = \max(F^*_{0,t} - F_{t,T}, 0) \tag{5.10}$$

where

$$F^*_{0,t} = F_{0,t} + C_{t,T}$$

where $F^*_{0,t}$ is the futures price that includes the storage cost $(C)$ , $F_{0,t}$ is the nearest futures contract price with a maturity date at $t$ and $F_{t,T}$ is the futures price at t with a maturity date at $T$. As in both research papers it is assumed that the spot price and the futures price are uncertainty variables, the closed form of this process is

$$CY_{t,T} = F_{0,t}N(d_1) - F_{t,T}N(d_2)$$

where

$$d_1 = \frac{\ln(\frac{F_{0,t}}{F_{t,T}}) + (\frac{\sigma_p^2}{2})(T-t)}{\sigma_p\sqrt{(T-t)}}$$

$$d_2 = \frac{\ln(\frac{F_{0,t}}{F_{t,T}}) - (\frac{\sigma_p^2}{2})(T-t)}{\sigma_p\sqrt{(T-t)}}$$

and

$$\sigma_p^2 = \sigma_{F_{0,t}}^2 + 2\sigma_{F_{0,t}}\sigma_{F_{t,T}}\rho_{F_{0,t}F_{t,T}} + \sigma_{F_{t,T}}^2$$

where $N()$ is the cumulative normal distribution, $\sigma$ is the volatility and $\rho$ is correlation coefficient. Lin and Duan point out that convenience yield is sensitive to seasonality from the business cycle, which affects demand and supply shocks. Inventory is also a key factor of variation in convenience yield. If inventory levels are high, the convenience yield is low, a similar finding to that of Samuelson (1965). Kocagil (2004) examines the daily convenience yield behaviour of crude oil, heating oil, gasoline, wheat, corn and copper. Convenience yield is calculated within a call option framework. Black and Scholes (1973) compare standard option pricing and exotic option pricing, with the assumption that the holder can exchange two underlying assets in the future so that the interest rate is not taken into account for the exotic options approach. The empirical results indicate that an exotic option approach is more appropriate for modelling the daily convenience yield than a standard call option formula. Moreover, two hypotheses have been tested. The first empirical results indicate that the convenience yield increases when the marginal production costs increase, and the second study shows contrasting results with Heinkel, Howe and Hughes (1990): a negative relationships between the convenience yield and price autocorrelation (AC (1)) are found; however, the longer lag of price autocorrelation (AC (5) and AC (20)) tests show a positive relationship, although these lags of price autocorrelation tests are insignificant.

### 5.2.2 Convenience Yield studies with other Variables

The study of convenience yield for storable commodities has continued during the last decade. The majority of the research examines the relationship between convenience yield and other variables such as spot prices, inventory levels, and production costs. Regression analysis is the main method for studying the relationship. For example, Routledge, Seppi, and Spatt (2000) show that a mixture of supply, demand and storage decisions gives rise to convenience yield. In particular, they present the relationship between storage levels and convenience yields. When

storage in the economy is driven to the lowest bound, convenience yields are relatively high. This provides the economic rationale for allowing convenience yield to depend on the spot price. Furthermore, they suggest that the spot price and the convenience yield should be time varying. The three-factor model seems to be the best predictor in continuous time because this model captures all the dynamics of the key variables.

However, Power and Turvey (2008) argue that for agricultural commodity futures, interest rate risk has a little effect and risk premiums are small and seldom significantly different from zero. They also examine the relationship of net convenience yield and the US inventory volume of wheat, soybeans and corn. A nonlinear relationship has been found for wheat and soybeans, but ambiguous results were obtained for corn. The net convenience yields of these three samples are approximated from the basic definition, which was introduced by Sorensen (2002). The convenience yield is estimated by

$$CY_t\left(T-t\right) = r_t\left(T-t\right) - \frac{\log F_t\left(T-t\right) - \log F_t\left(t\right)}{T-t} \tag{5.11}$$

where $r_t(T-t)$ is the interest rate over the period, $F_t(T-t)$ is the futures price and $F_t(t)$ is the spot commodity price. Sorensen employs a Kalman filter to estimate the maximum likelihood parameters of the state apace model of the futures price. The futures price is determined by taking the expectations of the martingale measurement to the spot price. The dynamic of agricultural spot price is modelled as a function of a sum of the deterministic seasonal component, the non-stationary state variable and a stationary state variable. Therefore, the convenience yield over next period is

$$CY_t\left(T-t\right) = r_t\left(T-t\right) - \frac{S\left(t+T-t\right) - S\left(t\right)}{T-t} - \frac{A\left(T-t\right)}{T-t} + \frac{1}{T-t}\left(1-\exp\left(-k(T-t)\right)\right)z_t \tag{5.12}$$

where $\frac{A(T-t)}{T-t}$ is the deterministic risk component, $z_t$ is the stationary state-variables.

There are many studies which show factors that affect convenience yield, such as inventory level, current price level and price volatility. Power and Turvey (2008) claim the changes in

inventory affect the dynamics of convenience yields. Convenience yield is highly responsive to inventory at low inventory levels (near stock-outs), but unresponsive to inventory changes at high inventory levels.

Pindyck (2004) demonstrates that convenience yields depend on the current price level, the price volatility and the level of the storage. Sorensen (2002) models seasonality in corn, soybeans and wheat futures prices, and gives empirical evidence on the theory of storage, which indicates that there is a strong negative relationship between the stock level and convenience yield. Dincerler et al. (2005) study the determining factors of convenience yields employing a hand-collected dataset of inventories to represent a relative scarcity of crude oil, natural gas, gold and copper. Unfortunately, the limited availability of inventory data sets prevents clear conclusions being reached. They attempt to investigate the convenience yield-price relationship by assuming a linear regression model; however, their results indicate a non-linear relationship between convenience yield and price.

### 5.2.3 Currency Exchange Rate Effect

This chapter focuses on the exchange rate effect on convenience yield. By the law of one price (LOP), identical products in two countries must have equivalent prices when adjusted by the exchange rate.

$$P_{i,t}^{d} = FX_t \times P_{i,t}^{f} \tag{5.13}$$

where $P_{i,t}^{d}$ is the domestic price product, $P_{i,t}^{f}$ is the foreign price product, and $FX_t$ is the exchange rate between two counties. The linkage between exchange rate movement and commodity prices has been studied. The main finding is that there is a significant relationship between them. For example, Chen and Rogoff (2003) demonstrate that commodity price effects shocked the real exchange rate in Australia, New Zealand and Canada. These three countries can be called commodity economies because of the high proportion of commodity income that makes up their total export revenues. More than 50 per cent of the export revenue

of New Zealand is generated from exporting commodity products; in addition, approximately 60 per cent of Australian export revenue comes from wool, wheat and other commodity products. Canada's revenue is comparatively less dependent than New Zealand's or Australia's on commodities, but their main export commodities, aluminium, copper, nickel, wood and crude oil, are important in the world market.

Another key factor that their paper examines is model specification: a deterministic trends and a stochastic trends processes are examined by ex/including trend in AR (1) process. The AR (1) process with stochastic trend seems to be an optimal model which is employed in the rest of their research. Hatzinikolaou and Polasek (2005) also examine the long-term relationship and short term relationship between a nominal exchange rate change and the commodity price index of Australia and the OECD. The Australian quarterly data consists of a 90-day bill rate, the Australian Consumer Price Index and the Index of Commodity Price. The 90-day Eurodollar rate and OECD-Total CPI from 1984:1-2003:1 are also used in their study by constructing a cointegration and error-correction models. The results indicate that an increase of commodity price led to a high demand for the floating Australian dollar that caused an appreciation of Australian dollar.

Akram (2009) demonstrates that devaluation in the real value of dollar causes a higher price in many commodities, such as Brent crude oil, metals, industrial raw materials and food, which are represented by the Economist's World Commodity Price Index in USD. The Vector autoregression (VAR) model is not only used to examine these relationships, but it also investigates whether interest rate and the real dollar exchange rate shocks lead to the fluctuation in commodity prices.

There have been many studies examining the effects of the exchange rate on import and export prices. Yeboah et al. (2009) examine the short-run dynamic of the US exchange rate against Mexico, in addition, the impact of exchange rate on 'non-farm products' such as chemicals, farm machinery, feed and fertilizers, is investigated in the US by using the LOP framework. The quarterly data of exchange rate from the Economic Research Service (ERS) of the USDA and the input prices from the National Agricultural Statistic Service (NASS) are

used in this empirical study. Their findings show that the LOP is rejected for all cases. Thus, input prices show no significant response to changes in the exchange rate. This conclusion is similar to that of Goldberg and Knetter (1997) who claim that the import prices have less reaction than the export prices to the exchange rate dynamic.

Baek and Koo (2010) state that changes in the exchange rate are an important element in the interrelation between the US farm income and other macroeconomic variables. They investigate the interaction of US farm income and four other macroeconomic variables, namely, agriculture price, GDP, interest rate and exchange rate, using the yearly data from 1957-2008. From their analysis, significant negative coefficients for exchange rates were found in long term and short term relationships. This implies that the depreciation of the US dollar offers increased income to the US farmer. GDP and interest rate variables are less important in showing the interrelationship than the exchange rate and the US agriculture price variable.

Yazici (2008) shows that the long-run and short-run relationships between the trade balance in Turkey, which consists of agriculture, manufacturing and mining, and the exchange rate have been found in the empirical analysis by using the Bahmani-Oskooee (1985) trade balance model. Estimation parameters indicate that the devaluation of Turkish lira against the US dollar was beneficial only in the manufacturing and mining sectors in the long term. For short term effect, trade balance increased at the beginning, but it decreased and rebounded at the final phase in all three sectors.

The effects of changes in the exchange rate on the export volume of agriculture from Taiwan to the USA between 1989 and 1999 is determined by Wang and Barrett (2007). They claim that the expected exchange rate volatility negatively affected only the agricultural export volume; no significant effect was indicated in any other sector of the Taiwanese economy. The main reasons for these findings are small agribusiness' inability to manage the exchange rate risk, and the lack of interest in the agricultural sector for using expensive farming aids, such as fertilizer, animal feed and pesticides. Although Taiwan's central bank provides a futures/forward contract on an exchange rate, the farmer cannot fully take advantage of this opportunity in the same way that producers can in other sectors.

Links between changes in the exchange rate and agricultural prices or volume has been documented. This review shows there are significant correlations between the convenience yield and the futures price, demand and supply. Therefore, the existence of a relationship between exchange rate changes and convenience yield is a reasonable hypothesis that can be tested in this chapter. According to the collected international futures prices used in this chapter, the effects of changes in the exchange rate on the world leading exporting countries must be considered in the context of how it affects the physical benefit of holding agricultural products. We believe that this is the first time that the convenience yield has been modelled using changes in the exchange rate as a covariate.

## 5.3 Data and Methodology

### 5.3.1 Data

This study uses seven agricultural futures contract prices, which have six different times to maturity. Daily data is collected from four leading commodity futures exchange markets. The rubber futures contract prices are gathered from the Tokyo Commodity Exchange Market (TOCOM), Japan. The white sugar futures contract prices are collected from LIFFE, London. The rough rice and corn futures contracts are traded on the Chicago Board of Trade (CBOT). The coffee, cotton and raw sugar futures contracts are traded on the New York Board of Trade (NYBOT). The required data is not only the futures contract prices but also the risk free interest rate. The interbank 3 month offer rate of different futures exchange markets locations are used as a risk free rate that consists of the US interbank rate, the UK interbank rate and the Japan interbank rate.

Table 5.1 gives a statistical summary of all the agriculture futures contracts. These contracts have 6 different maturity dates which cover the period of 1990 to 2010. However, the numbers of observations differ depending on the number of open days of each futures market. The different number of trading days to maturity date has an effect on futures prices and

net convenience yield. The information provided in Table 5.2 has been used to estimate the number of trading days. This information was gathered from the futures exchange market website.

The final part of this study determines the currency effect on net convenience yield. There are three commodities, rubber, white sugar and raw sugar, are carried on from this section to final part. Due to the changes in the exchange rate regime in Thailand, the managed-float exchange rate regime was introduced in 1997 during the Asian financial crisis. The exchange rate between 1998 and 2010 are used to study the currency effect; however, the Euro currency data set is taken from 2000.

### 5.3.2 Methodology

This part explains the methods of net convenience yield modelling. In the first section of this chapter, the backwardation approach is used to calculate the net convenience yield. Then, heteroskedasticity tests were provided, which consist of four existing tests. In addition, we proposed a new heteroskedasticity test. The net convenience yield is constructed in the later part; moreover, various time varying volatility processes and probability density functions were demonstrated.

#### 5.3.2.1 Net Convenience Yield

The net convenience yield is a crucial component in the futures price formula introduced by Kaldor (1939) and Working (1948,1949) as shown in equation 5.14. This formula is acceptable in the market, and it is used as a standard formula to calculate the storable futures contract price.

$$F_t = S_0 \exp^{(r+s-y)(T-t)} \tag{5.14}$$

where $F_t$ is a futures price, $S_0$ is a spot price (the nearest futures contract prices), $T-t$ is

Table 5.1: Statistic of summary descriptions of all futures contracts prices

| **Coffee** | | | | | | | **Rough Rice** | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Max | 314.80 | 273.80 | 244.25 | 244.00 | 244.40 | 245.40 | Max | 24.46 | 24.82 | 22.43 | 22.18 | 22.38 | 22.58 |
| Min | 41.50 | 45.15 | 46.70 | 48.15 | 49.30 | 51.25 | Min | 3.43 | 3.64 | 3.85 | 4.07 | 4.28 | 4.49 |
| Std | 40.49 | 38.41 | 36.58 | 35.28 | 34.29 | 33.47 | Std | 3.29 | 3.25 | 3.17 | 3.12 | 3.06 | 2.98 |
| Mean | 105.98 | 106.94 | 108.00 | 109.15 | 110.34 | 111.61 | Mean | 8.75 | 8.86 | 8.95 | 9.02 | 9.05 | 9.10 |
| Observations | 5257 | | | | | | Observations | 5255 | | | | | |
| **Corn** | | | | | | | **White Sugar** | | | | | | |
| Max | 754.75 | 768.25 | 788 | 805 | 813 | 815.75 | Max | 826.40 | 802.70 | 774.10 | 711.60 | 650.40 | 619.80 |
| Min | 174.75 | 182.5 | 187.25 | 190.5 | 197 | 206.25 | Min | 160.80 | 163.50 | 163.50 | 167.20 | 167.60 | 167.60 |
| Std | 93.8839 | 93.7293 | 93.7361 | 93.0637 | 92.0669 | 91.6653 | Std | 108.69 | 105.16 | 99.65 | 93.77 | 89.74 | 87.42 |
| Mean | 281.22 | 286.93 | 291.78 | 295.37 | 297.72 | 300.48 | Mean | 312.69 | 306.93 | 303.18 | 299.48 | 297.33 | 295.58 |
| Observations | 5255 | | | | | | Observations | 5337 | | | | | |
| **Cotton** | | | | | | | **Raw Sugar** | | | | | | |
| Max | 159.12 | 147.11 | 143.54 | 139.80 | 123.49 | 99.99 | Max | 34.39 | 30.77 | 27.18 | 25.15 | 23.76 | 22.47 |
| Min | 28.52 | 30.22 | 31.25 | 32.25 | 34.00 | 34.95 | Min | 4.50 | 4.08 | 4.56 | 5.03 | 5.08 | 5.20 |
| Std | 16.77 | 14.93 | 13.46 | 12.25 | 11.16 | 10.30 | Std | 4.31 | 4.17 | 3.89 | 3.68 | 3.54 | 3.38 |
| Mean | 64.28 | 64.77 | 65.17 | 65.44 | 65.69 | 66.06 | Mean | 10.81 | 10.77 | 10.63 | 10.53 | 10.50 | 10.46 |
| Observations | 5257 | | | | | | Observations | 5257 | | | | | |
| **Rubber** | | | | | | | | | | | | | |
| Max | 455.40 | 412.80 | 414.40 | 416.00 | 417.00 | 417.60 | | | | | | | |
| Min | 53.80 | 56.30 | 58.00 | 60.00 | 61.00 | 62.00 | | | | | | | |
| Std | 75.79 | 73.83 | 72.72 | 71.88 | 71.44 | 71.50 | | | | | | | |
| Mean | 147.30 | 147.33 | 147.59 | 148.01 | 148.68 | 149.54 | | | | | | | |
| Observations | 5145 | | | | | | | | | | | | |

Table 5.2: Contract descriptions

| **Coffee** | |
|---|---|
| Exchange Market | Intercontinental Exchange (NYBOT: ICE) |
| Contract Listing | March, May, July, September and December |
| Expiry Date | Seven business days prior to the first business day of delivery month |
| **Corn** | |
| Exchange Market | Chicago Board of Trade (CBOT) |
| Contract Listing | March, May, July, September and December |
| Expiry Date | A business day prior to the 15th calendar day of the contract month |
| **Cotton** | |
| Exchange Market | Intercontinental Exchange (NYBOT: ICE) |
| Contract Listing | March, May, July, October and December |
| Expiry Date | Seventeen days before the last business day of delivery month |
| **Rubber** | |
| Exchange Market | Tokyo Commodity Exchange (TOCOM) |
| Contract Listing | Every Month |
| Expiry Date | The last business day of the contract month, except December( the 28th for December) |
| **Rough Rice** | |
| Exchange Market | Chicago Board of Trade (CBOT) |
| Contract Listing | January, March, May, July, September and November |
| Expiry Date | A business day prior to the 15th calendar day of the contract month |
| **White Sugar** | |
| Exchange Market | NYSE Liffe London |
| Contract Listing | March, May, August, October, and December |
| Expiry Date | Sixteen days before the first day of delivery month |
| **Raw Sugar** | |
| Exchange Market | Intercontinental Exchange (NYBOT: ICE) |
| Contract Listing | March, May, July and October |
| Expiry Date | First business day after last business day of the previous delivery month |

*This information can be found in the contract specifications provided by the commodity exchange markets.

days to maturity,$r$ is the risk free over the period, $s$ is the storage cost and $y$ is the convenience yield.

We assume a net convenience yield which is composed of the storage cost and the convenience yield. The main reason for involving storage as an unknown variable is that there is a major difficulty with data collection and unreliable data sources. For example, the storage cost of rubber should be collected from Thailand as a world leading exporter and the largest production area, but unfortunately, the secondary data is unavailable. Therefore, the futures pricing is

$$F_t = S_0 \exp\left(r - NCY_t\right)(T-t) \tag{5.15}$$

The net convenience yield is estimated by the backwardation method as shown in the following equation

$$NCY_t = r_t - \frac{1}{(T-t)} \ln\left(\frac{F_t}{S_0}\right) \tag{5.16}$$

Six different maturity contract prices are collected. We take the nearest futures contract price as the spot price; thus, there are five net convenience yield series for the agricultural commodities.

#### 5.3.2.2 Net Convenience Yield Modelling

After the net convenience yield is estimated from equation 5.16, the next step before modelling is the examination of heteroskedasticity. The heteroskedasticity test is a very important linear regression model with high-frequency time series data (Green, 2008). In addition, the optimal method of calibrating the net convenience model is also required to provide precise estimations. The ordinary least square is a simple method to calibrate the linear regression: the prerequisites of the OLS method is the error term must be homoskedasticity and serially uncorrelated, otherwise, the estimations are biased. Therefore, our model must be checked against heteroskedasticity so as to find a suitable calibration to calibrate the net convenience

modelling.

The net convenience yield modelling begins with AR(1) process derived from the concept of in a relationship between the level and volatility of the net convenience yield shown by Liu and Tang (2011). Their study formula is

$$NCY_t - NCY_{t-1} = \mu + \gamma(NCY_{t-1}) + \varepsilon_t \tag{5.17}$$

The linear regression in 5.17 can be rearranged as equations 5.18. This model is an AR(1) process, which comprises a constant and a previous lagged of the net convenience yield with $1 + \gamma$ coefficient.

$$NCY_t = \mu + (1 + \gamma)(NCY_{t-1}) + \varepsilon_t \tag{5.18}$$

#### 5.3.2.3 Heteroscadasticity Test

In the ordinary least square (OLS) procedure, the assumptions of a residual term are the time constant variation and independence and identically distribution (iid). The residual term of our net convenience yield model is

$$\varepsilon_t = NCY_t - \mu - (1 + \gamma)NCY_{t-1} \tag{5.19}$$

Thus, the assumption of constant time variance is defined as

$$V(\varepsilon_t) = \sigma^2_{\varepsilon_t} = \sigma^2$$

Five heteroskedasticity tests are used to show the existence of the required assumption of OLS. The main reason for employing several tests is that there are different intuitions behind each heteroskedasticity test. However, all of these models are based on the null hypothesis that

$$H_0 : \sigma^2_{\varepsilon_t} = \sigma^2 = Homoskedasticity$$

$$H_a : \sigma_{\varepsilon_t}^2 \neq \sigma^2 = Heteroskedasticity$$

A heteroskedasticity test of Breusch-Pagan (1979), as shown in equation 5.20 begins this section. They state that the residual term from the ordinary least square method is a function of some known variable that employs the level of net convenience to demonstrate this test. The estimation of Breusch-Pagan is based on the Lagrangian multiplier test.

$$\varepsilon_t^2 = \kappa_{BPG} + \phi_{BPG}\left(NCY_{t-1}\right) + \eta_t \tag{5.20}$$

Another heteroskedasticity test employed in this study is Glejser (1969), as shown in equation 5.21. This test demonstrates the linear relationship between the absolute value of the residual term and the level of the net convenience yield. They document that the acceptance of non negative $\kappa_G$ and $\phi_G$ is called mixed heteroskedasticity. The determined value is based on the weighted least-squares.

$$\mid \varepsilon_t \mid = \kappa_G + \phi_G\left(NCY_{t-1}\right) + \eta_t \tag{5.21}$$

The third heteroskedasticity test is Harvey (1976). Non-linear regression is introduced as an alternative approach to the general heteroskedasticity test that usually estimates the linear regression model. The simple equation of Harvey, which demonstrates the relationship between the logarithm of the residual term, is obtained through OLS and the level of the net convenience yield is shown in equation 5.22. The maximum likelihood estimation is used to calibrate parameters, and the likelihood ratio test is used to determine heteroskedasticity.

$$\log\left(\varepsilon_t^2\right) = \kappa_H + \phi_H\left(NCY_{t-1}\right) + \eta_t \tag{5.22}$$

The following test is ARCH test, it has been studied since its introduction by Engle (1982). The conditional variance is a function of previous error terms, as seen in the formula below:

$$\sigma_t^2 = \omega + \alpha_{ARCH}\varepsilon_{t-1}^2 \tag{5.23}$$

where $\sigma_t^2$ is the conditional variance at $t$, $\varepsilon_{t-1}$ is the previous residual term, $\omega$ is the

constant, and $\alpha_{ARCH}$ is the coefficient of the previous error term. The significant of $\alpha_{ARCH}$ imply to the heteroskadasticity.

The final test is modified from the concept of GARCH(1,1) heteroskadasticity test that is found in Liu and Tang (2011). They explain that conditional volatility is computed from the GARCH (1,1) process is better than the residual term from the linear regression model which might not be efficientive at giving the precise solutions. Therefore, the variance in 4.4 is compute from GARCH (1,1) as following

$$\sigma^2_{G(1,1),t} = \omega_{G(1,1)} + \alpha_{G(1,1)}\sigma^2_{G(1,1),t-1} + \beta_{G(1,1)}\varepsilon^2_{t-1}$$

$$\sigma^2_{G(1,1),t} = \kappa_{G(1,1)} + \phi_{G(1,1)}\left(NCY_{t-1}\right) + \eta_t \tag{5.24}$$

This test shows the concept that the heteroskedasticity may be tested by using both the level and the disturbance term. We call this test the combined test (C-Test). We assume that the residual term from the OLS procedure is a linear function of the level of net convenience yield, and the last lagged residual term is written as equation 5.25. The ordinary least square is utilised for this estimation. The acceptance of either hypothesis $\phi_M = 0$ or $\varphi_M = 0$ leads to the rejection of a null hypothesis. This indicates the existence of heteroskedasticity.

$$\varepsilon^2_t = \kappa_C + \phi_C\left(NCY_{t-1}\right) + \varphi_C\left(\varepsilon^2_{t-1}\right) + \eta_t \tag{5.25}$$

An alternative method of estimation, if heteroskedasticity has been found, is maximum likelihood estimation. Maximum likelihood estimation relies on a probability distribution function. For Gaussian error distribution, the maximization of the logarithm likelihood function is

$$\max \ln L = \max \Sigma^T_{t=1} \ln\left(l_t\right) = \max \Sigma^T_{t=1}\left[-\frac{1}{2}\ln\left(2\pi\right) - \frac{1}{2}\ln\left(\sigma^2\right) - \frac{1}{2}\frac{y^2_t}{\sigma^2_t}\right] \tag{5.26}$$

If high kurtosis has been found in the data analysis, it implies a fat tail distribution of the random data. In this case, it is better to calibrate with a probability distribution that can capture the fat tail feature rather than with the Gaussian model. Standardised-t error distribution is a simple probability density function, and it is also popular in many commodity

modelling studies. Hence, Standardised-t distribution probability density function is used in the calibration. These two error distributions are already explained in 4.3.2.

Moreover, time varying volatility has been set as a requirement for the maximum likelihood estimation. This chapter assumes two possible time varying volatility models: Generalized Autoregressive Conditional Heteroscedasticity (GARCH) and Intergrated Generalized Autoregressive Conditional Heteroscedasticity (IGARCH). GARCH (1,1) is a simple time varying volatility model created by Bollerslev (1986) and is employed and explained in Chapter 4.

$$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \tag{5.27}$$

The alternative time varying volatility model is IGARCH (1,1) that was introduced by Lamoureux and Lastrapes (1990). IGARCH (1,1) is a special version of GARCH (1,1),as the constraint of IGARCH is $\alpha + \beta = 1$ and $\beta > 0$. The IGARCH (1,1) process is as follows

$$\sigma_t^2 = \omega + (1 - \beta_1)\varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \tag{5.28}$$

## 5.4 Empirical Results

### 5.4.1 Net Convenience Yield Behavior

Table 5.3 represents the basic statistic descriptions of the net convenience yield each of the seven agricultural products have six different contracts. Therefore, there are five net convenience yield series of each agricultural product. The differences between the maximum and minimum prices are very small, and the variances are also very low. In addition, most of the skewness are positive and closed to zero when have longer time to maturity, except raw sugar net convenience yield that have negative skewness. The kurtosis values of all agricultural commodities are very high, especially the net convenience yield of the nearest futures contract. These imply the leptokurtotic distribution.

Table 5.3: Descriptive statistics of net convenience yield for seven commodities

| **Coffee** | | | | | | **Rough Rice** | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Max | 0.0027 | 0.0022 | 0.0021 | 0.0020 | 0.0019 | Max | 0.0040 | 0.0022 | 0.0013 | 0.0013 | 0.0013 | 0.0014 |
| Min | -0.0009 | -0.0007 | -0.0006 | -0.0006 | -0.0004 | Min | -0.0048 | -0.0024 | -0.0016 | -0.0011 | -0.0011 | -0.0012 |
| Std | 0.0004 | 0.0004 | 0.0004 | 0.0004 | 0.0004 | Std | 0.0005 | 0.0004 | 0.0004 | 0.0004 | 0.0004 | 0.0005 |
| Skewness | 2.1191 | 1.8301 | 1.5256 | 1.2366 | 0.9671 | Skewness | 0.4780 | 0.6317 | 0.2983 | 0.0001 | 0.0001 | -0.2899 |
| Excess Kurtosis | 10.2060 | 7.6244 | 6.1741 | 4.9576 | 3.9802 | Excess Kurtosis | 19.1492 | 5.6965 | 3.5678 | 3.0317 | 3.0317 | 3.0101 |
| **Corn** | | | | | | **White Sugar** | | | | | | |
| Max | 0.0044 | 0.0035 | 0.0025 | 0.0019 | 0.0017 | Max | 0.0052 | 0.0033 | 0.0024 | 0.0026 | 0.0026 | 0.0030 |
| Min | -0.0009 | -0.0006 | -0.0005 | -0.0004 | -0.0004 | Min | -0.0011 | -0.0008 | -0.0005 | -0.0003 | -0.0003 | -0.0002 |
| Std | 0.0004 | 0.0004 | 0.0003 | 0.0003 | 0.0004 | Std | 0.0004 | 0.0004 | 0.0004 | 0.0004 | 0.0004 | 0.0004 |
| Skewness | 4.4223 | 3.4843 | 2.2930 | 1.1807 | 0.7030 | Skewness | 1.7303 | 0.8490 | 0.7138 | 0.9307 | 0.9307 | 1.2054 |
| Excess Kurtosis | 40.0678 | 23.5132 | 12.2166 | 5.4021 | 3.4767 | Excess Kurtosis | 10.1839 | 4.8419 | 4.0479 | 4.4720 | 4.4720 | 5.3821 |
| **Cotton** | | | | | | **Raw Sugar** | | | | | | |
| Max | 0.0038 | 0.0025 | 0.0021 | 0.0018 | 0.0017 | Max | 0.0036 | 0.0020 | 0.0027 | 0.0013 | 0.0013 | 0.0015 |
| Min | -0.0016 | -0.0010 | -0.0007 | -0.0005 | -0.0005 | Min | -0.0026 | -0.0014 | -0.0022 | -0.0007 | -0.0007 | -0.0005 |
| Std | 0.0004 | 0.0004 | 0.0004 | 0.0004 | 0.0004 | Std | 0.0004 | 0.0004 | 0.0004 | 0.0003 | 0.0003 | 0.0004 |
| Skewness | 2.1504 | 1.7683 | 1.2631 | 0.8915 | 0.5698 | Skewness | 0.5402 | -0.0265 | -0.5278 | -0.1658 | -0.1658 | -0.1196 |
| Excess Kurtosis | 16.0605 | 8.2691 | 5.4581 | 3.9201 | 3.0026 | Excess Kurtosis | 6.5935 | 3.4876 | 7.5706 | 2.7729 | 2.7729 | 2.5873 |
| **Rubber** | | | | | | | | | | | | |
| Max | 0.0103 | 0.0058 | 0.0044 | 0.0034 | 0.0027 | | | | | | | |
| Min | -0.0049 | -0.0032 | -0.0024 | -0.0021 | -0.0017 | | | | | | | |
| Std | 0.0009 | 0.0007 | 0.0006 | 0.0006 | 0.0005 | | | | | | | |
| Skewness | 2.6943 | 1.7191 | 1.3242 | 1.0742 | 0.8540 | | | | | | | |
| Excess Kurtosis | 24.3554 | 10.9250 | 7.6019 | 6.2423 | 5.3656 | | | | | | | |

Figure 5.1: Histogram of coffee net convenience yield

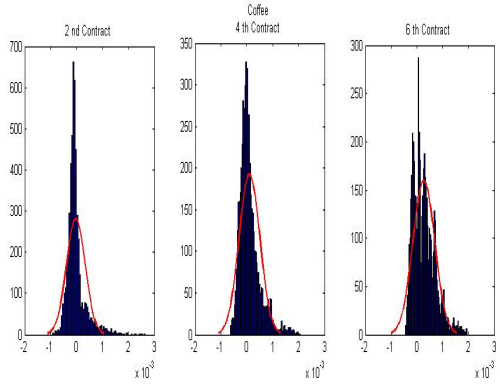



Figure 5.2: Histogram of corn net convenience yield

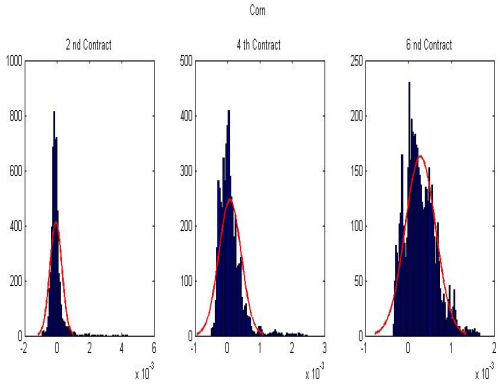



Figure 5.1 shows a histogram compared with a fitted normal distribution. The red line is a normal distribution curve, and the blue histogram is the net convenience yield. These figures are drawn by the histfit function in Matlab. This function produces a normal distribution curve and histograms of data. The graphics strongly demonstrated evidence of fat-tailed distribution in all data, especially in the longer time to maturity. For example, in the histogram of coffee, the 6th contract net convenience yield is larger than the 2nd contract net convenience yield.

Figure 5.3: Histogram of cotton net convenience yield

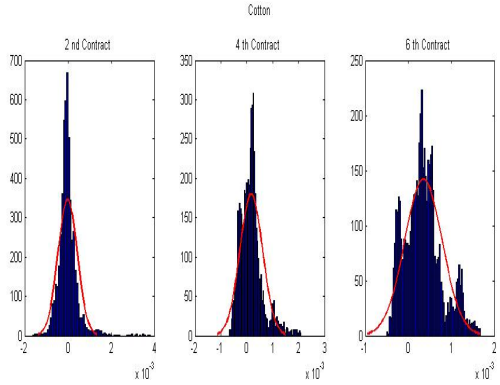



Figure 5.4: Histogram of rubber net convenience yield

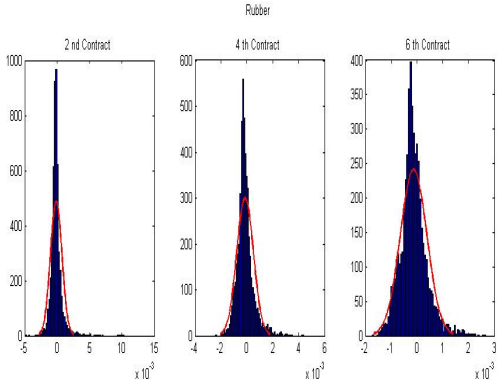



Figure 5.5: Histogram of rough rice net convenience yield

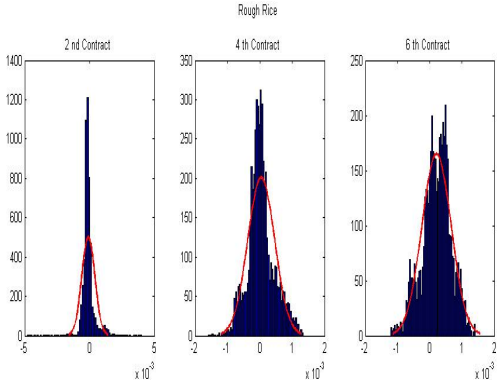


Figure 5.6: Histogram of white sugar net convenience yield

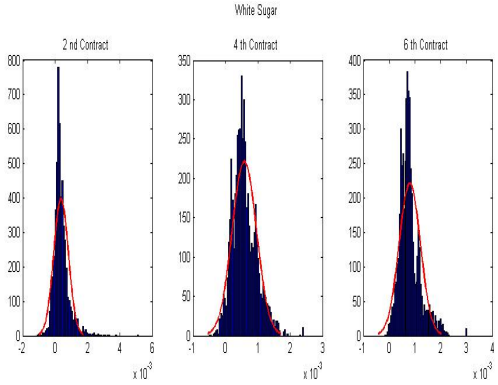



Figure 5.7: Histogram of raw sugar net convenience yield

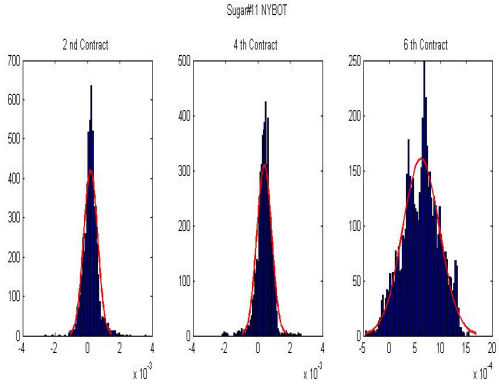


Figure 5.8 demonstrates the net convenience term structure. We plotted the graph to include 366 days; however, the beginning period is seemingly a problem for generating the term structure. According to the estimation set-up, we assume the nearest maturity futures price is the spot price; therefore, the net convenience yield of the 30 days of rubber and 60 days of the other agricultural products are undefined.

The net convenience yield is define as

$$NCY = Convenience\,Yield - Storage\,Cost \tag{5.29}$$

We have found two main explanations from the empirical net convenience yield. Firstly, a similarity in the patterns of net convenience yield term structure and futures price was discovered. For instance, the sugar futures price curve is in backwardation since a cheaper futures contract has been found at a longer maturity. These patterns directly affect the net convenience yield term structure, as the net benefit of holding a physical agricultural product decreases during a long period. In reality, there is a low demand for holding the physical commodity. The other agriculture net convenience term structures are similar as the result of the identical futures curves which are in a contango. The contango indicates that the futures prices are higher than the spot price. The increase of net convenience yield has been detected in up to a 180 days contract; however, the long term maturity futures price is not affected by the net convenience yield. This implies that the benefit of physically holding the commodity is approximately equal to the cost of storage.

Secondly, the relationship between the net convenience yield and the storage cost is explained from empirical findings. The empirical net convenience yield shows both positive and negative values. Thus, there are two cases of net convenience yield term structure as shown in the following,

Case I : Negative Net Convenience Yield

$$Convenience\,Yield - Storage\,Cost < 0$$

The interpretation of negative net convenience yield indicates that the storage cost is higher than the convenience yield. We have found negative net convenience yield in contago. This finding implies that the benefit of holding the physical agricultural commodity cannot be fully taken due to the high storage costs. However, longer maturity net convenience yield approaches to zero. This shows that with increasing convenience yield, the storage costs decrease, causing a lower supply in the market because farmers prefer to hold the commodity. The longer maturity futures prices are higher than the shorter the maturity, as we can see in the contango.

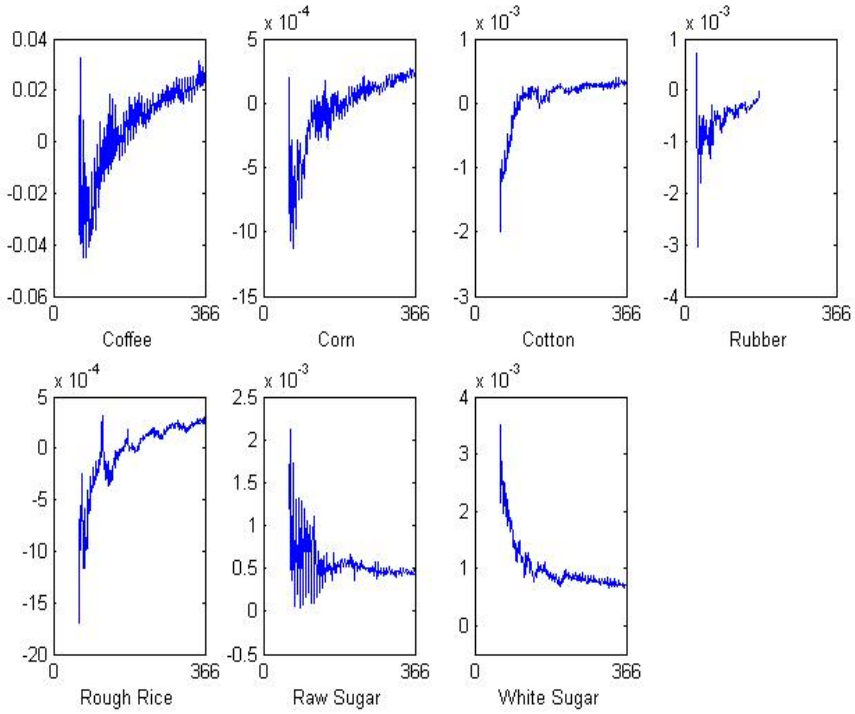
Case II : Positive Net Convenience Yield

$$Convenience\,Yield - Storage\,Cost > 0$$

The positive net convenience yield indicates that the benefit of the physical holder of an agricultural commodity is higher than the storage cost, but the convenience yield decreases the longer the maturity futures contract. In the meantime, the storage costs increase, which causes the net convenience yield to come close to zero. This finding implies that there is no benefit from holding the agricultural commodity in the long term, as the price goes into backwardation.

Moreover, a similar characteristic of long term net convenience yield is approaching zero. Therefore, we can conclude that the convenience yield will be offset by storage costs in the long term futures contract.

Figure 5.8: Convenience yield term structure




### 5.4.2 Empirical Tests of the Heteroskedasticity

This part explains the heteroskedasticity tests used in this thesis: the Breusch-Pagan test (BP), Glejser test, Harvey test, ARCH test, and a combined test of second, fourth and sixth futures contracts for all agricultural commodities.

Tables 5.4 to 5.6 represent the results of all heteroskedasticity tests of second, fourth and sixth futures contracts. The regression coefficients are provided, and the p-value is illustrated in the parenthesises. The null hypothesis is a homoskedastic in the model at 5 per cent significance level. The empirical results indicate that most of the agricutural futures contracts prices are heteroskedatic. For example, the Breusch-Pagan test (BP), the Glejser test and the Harvey test of all seven agricultural commodities of second futures contracts all show their p-values are zero, this means that the data is heteroskedastic. However, the ARCH tests present the homoskedasticity of corn's and cotton's second futures contracts as acceptance of null hypotheses found. In addition, the combined test calibrates similar results, as show in

the homoskedasticity if we look at the residual variable, but the p-value is small at lagged variables. The combined test, therefore, indicates heteroskedasticity.

The fourth results are shown in Table 5.5. The Breusch-Pagan test (BP), the Glejser test, and the Harvey test also generate zero p-values for all agricultural commodities that are similar to the second futures contracts. This implies that the data is heteroskedastic. However, the ARCH test shows acceptances of null hypotheses in fourth futures contracts of corn, cotton, rough rice and raw sugar, which indicates homoskedasticity. The combined test of corn, cotton, rough rice and raw sugar prices also generates a high p-value for residual variables greater than 0.05, but the p-values of the lagged variables are smaller than 0.05 except in the case of raw sugar. Thus, the corn and rough rice forth futures contracts are heteroskedastic, on the other hand, the raw sugar forth futures contract is homoskedastic.

Finally, the sixth futures contract results shown in Table 5.6 present similar results for all agricultural commodities using the Breusch-Pagan test (BP), the Glejser test and the Harvey test. These show heteroskedasticity; however, ARCH tests still indicate the homoskedasticity of corn, cotton and rough rice. The combined test of both lagged and residual variables confirm the homoskedasticity of cotton and rubber but show heteroskedasticity in corn because the lagged variable is rejected.

Therefore, only one test of heteroskedaticity would not be sufficient evidence to conclude the existence of heteroskedasticity, and the combined test evidences the ability to capture both considered variables in a heteroskedasticity test. Heteroskedasticity is found if either lagged or residual variables are rejected. From the heteroskedasticity tests, most of our samples are heteroskedastic and would thus benefit from the use of a maximum likelihood estimation.

Table 5.4: Heteroskedasticity tests for all second contracts

| Second Contract | BP | Glejser | Hervey | ARCH | C-Test (NCY) | C-Test (Residual) |
|---|---|---|---|---|---|---|
| Coffee | 0.0000 | 0.0514 | 1572.6360 | 0.2806 | 0.0000 | 0.2453 |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| Corn | 0.0000 | 0.0538 | 1286.5280 | 0.0246 | 0.0000 | -0.0129 |
| | (0.0000) | (0.0000) | (0.0000) | (0.0743)* | (0.0000) | (0.3465)* |
| Cotton | 0.0001 | 0.0275 | 358.8961 | 0.0162 | 0.0001 | 0.0071 |
| | (0.0000) | (0.0000) | (0.0000) | (0.2394)* | (0.0000) | (0.6064)* |
| Rubber | 0.0005 | 0.1251 | 306.9510 | 0.1657 | 0.0005 | 0.1144 |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| Rough Rice | 0.0000 | 0.0377 | 787.4072 | 0.0608 | 0.0000 | 0.0584 |
| | (0.0046) | (0.0000) | (0.0000) | (0.0000) | (0.0109) | (0.0000) |
| Raw Sugar | 0.0001 | 0.0395 | 247.2035 | 0.2169 | 0.0001 | 0.2141 |
| | (0.0000) | (0.0000) | (0.0046) | (0.0000) | (0.0000) | (0.0000) |
| White Sugar | 0.0001 | 0.0816 | 1194.6030 | 0.2921 | 0.0001 | 0.2769 |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) |

Table 5.5: Heteroskedasticity tests for all fourth contracts

| Forth Contract | BP | Glejser | Hervey | ARCH | C-Test (NCY) | C-Test (Residual) |
|---|---|---|---|---|---|---|
| Coffee | 0.0000 | 0.0210 | 1432.7940 | 0.0623 | 0.0000 | 0.0491 |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0004) |
| Corn | 0.0000 | 0.0238 | 1467.8980 | 0.0056 | 0.0000 | -0.0090 |
| | (0.0000) | (0.0000) | (0.0000) | (0.6836)* | (0.0000) | (0.5132)* |
| Cotton | 0.0000 | 0.0105 | 535.2837 | 0.0063 | 0.0000 | 0.0041 |
| | (0.0000) | (0.0000) | (0.0000) | (0.6493)* | (0.0000) | (0.7675)* |
| Rubber | 0.0001 | 0.0401 | 279.3591 | 0.0646 | 0.0001 | 0.0537 |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0001) |
| Rough Rice | 0.0000 | 0.0115 | 575.8739 | 0.0212 | 0.0000 | 0.0191 |
| | (0.0085) | (0.0000) | (0.0000) | (0.1241)* | (0.0110) | (0.1661)* |
| Raw Sugar | 0.0000 | -0.0106 | -363.5561 | 0.0071 | 0.0000 | 0.0063 |
| | (0.0880)* | (0.0002) | (0.0000) | (0.6067)* | (0.0913)* | (0.6502)* |
| White Sugar | 0.0000 | 0.0175 | 588.7656 | 0.1654 | 0.0000 | 0.1588 |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) |

Table 5.6: Heteroskedasticity tests for all sixth contracts

| Sixth Contract | BP | Glejser | Hervey | ARCH | C-Test (NCY) | C-Test (Residual) |
|---|---|---|---|---|---|---|
| Coffee | 0.0000 | 0.0147 | 1280.9710 | 0.0462 | 0.0000 | 0.0322 |
| | (0.0000) | (0.0000) | (0.0000) | (0.0008) | (0.0000) | (0.0201) |
| Corn | 0.0000 | 0.0074 | 840.0683 | 0.0117 | 0.0000 | 0.0073 |
| | (0.0001) | (0.0000) | (0.0000) | (0.3970)* | (0.0001) | (0.5977)* |
| Cotton | 0.0000 | 0.0036 | 351.2956 | 0.0109 | 0.0000 | 0.0098 |
| | (0.0218) | (0.0000) | (0.0000) | (0.4282)* | (0.0233)* | (0.4793)* |
| Rubber | 0.0000 | 0.0198 | 184.9621 | 0.0688 | 0.0000 | 0.0634 |
| | (0.0000) | (0.0000) | (0.0075)* | (0.0000) | (0.0000) | (0.0000) |
| Rough Rice | 0.0000 | -0.0027 | -177.4270 | 0.0152 | 0.0000 | 0.0150 |
| | (0.1829)* | (0.0245) | (0.0251) | (0.2714)* | (0.1864)* | (0.2763)* |
| Raw Sugar | 0.0000 | -0.0058 | -540.1890 | 0.0582 | 0.0000 | 0.0581 |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0006) | (0.0000) |
| White Sugar | 0.0000 | 0.0128 | 430.3673 | 0.0268 | 0.0000 | 0.0164 |
| | (0.0000) | (0.0000) | (0.0000) | (0.0501)* | (0.0000) | (0.2329)* |

### 5.4.3 Net Convenience Modelling

This section explains the calibration of the AR (1) net convenience yield model as shown in equation 5.18. In this calibration, we assume two error distributions, Gaussian and Standardised-t error distribution, and two time volatility processes, GARCH (1,1) and IGARCH (1,1) as shown in equations 5.27 and 5.28. The equation 5.18 is rewritten with an appropriated variables as

$$NCY_t = \mu + (1 + \beta_2)(NCY_{t-1}) + \varepsilon_t \tag{5.30}$$

Table 5.7 represents the net convenience yield estimations for coffee. The tables contain an estimation of GARCH (1,1) with both Gaussian and Standardised-t error distribution, and IGARCH (1,1) with both Gaussian and Standardised-t error distribution, in addition the maximum likelihood ratio test used to evaluate the estimation performances.

The top section of this table shows the regression coefficients of GARCH (1,1) with both Gaussian and Standardised-t error distribution. The maximum likelihood ratio test indicates that the estimation of GARCH (1,1) with Standardised-t error distribution outperforms in all three types of futures contracts. For example, all parameters, $\omega$, $\alpha$ and $\beta_1$ ,of the GARCH

(1,1) process for the second futures contract are significant at 5 per cent significance level, and also the significant parameters, $\mu$ and $\beta_2$, of the AR (1) net convenience yield process are found. The degree of freedom ($v$) of Standardised-t error distribution is also significant, and these are 2.85, 2.42 and 2.83 for second, fourth and sixth futures contracts.

Moreover, the likelihood ratio test is computed between the Gaussian and Standardised-t error distribution. These numbers are exhibited below the GARCH (1,1) calibration part. The critical value of one degree of freedom is 3.8415, which is lower than our likelihood ratio. For example, the likelihood ratio tests are 2761, 4161 and 3480 for second, fourth and sixth futures contracts. The rejection of a null hypothesis, indicating that the unrestricted model is better than the restricted model, have been found for all three contracts. Therefore, these findings imply that the estimation with Standardised-t error distribution outperforms.

In addition, the lower part of the table shows the calibrations with IGARCH (1,1) and with Gaussian and Standardised-t error distributions. All coefficients of second futures contracts are significant at 5 per cent significance level. However, the constants of the IGARCH (1,1) process are insignificant as they are the same as the constants of the GARCH (1,1) process for the fourth and sixth contracts. The likelihood ratio tests two error distributions of IGARCH (1,1). Calibrations are provided that clearly indicate that the calibration with IGARCH (1,1) and Standardised-t error distribution outperforms. For example, the likelihood ratio tests are 4053, 4570 and 4160 for second, fourth and sixth futures contracts which are higher than the critical value (3.8415). The degree of freedom ($\nu$) numbers of standardised-t error distribution are significant, and they are 2.66, 2.46 and 3.46 for second, fourth and sixth futures contracts. The ratio tests seem quite dramatic, Standardised-t is likely to be better than the Gaussian error distribution.

A comparison between GARCH (1,1) and IGARCH (1,1) is also investigated. Only Standardised-t error distributions are considered because the Standardised-t error distribution estimations seem superior regarding our likelihood ratio test. The likelihood ratio test between GARCH (1,1) and IGARCH (1,1) is shown in the bottom of the table. The loglikelihood ratio tests are 26, 210 and 187 which lead to the rejection of an estimation with IGARCH

(1,1). The constraint on $\alpha$ and $\beta_1$ that is equal to one do not show any benefit in estimation. Therefore, the calibration with GARCH (1,1) and Standardised-t error distribution is better than the other assumptions for coffee futures net convenience yield.

The other agricultural commodities futures contracts estimations for corn, cotton, rough rice, rubber, white sugar and raw sugar are shown in Tables B.1 to B.6 respectively. All tables have the same presentation as the GARCH (1,1) with Gaussian and Standardised-t error distributions results are shown in the top section, and the lower part shows the IGARCH (1,1) calibrations of both error distributions. The parameters of GARCH (1,1) – $\alpha$ and $\beta_1$- and IGARCH (1,1) - $\beta_1$-are significant for all samples. In addition, the degree of freedom ($\nu$) numbers of standardised-t error distribution are also significant. Unfortunately, some constant parameters of both volatility processes are insignificant. The AR (1) coefficient parameters of all agricultural commodities are significant at 5 per cent significance level.

In conclusion, while heteroscadasiticity exists, we use the maximum likelihood estimation (MLE) procedure. Two- time varying volatility model, GARCH (1,1) and IGARCH (1,1), are assumed. Furthermore, Gaussian and Standardised-t error distribution are used to compare the ability to capture fat-tailed behaviour. The empirical results show that the GARCH (1,1) with Standardised-t error distribution outperforms.

### 5.4.4 Currency Exchange Rate Effect on the Agriculture Net Convenience Yield.

In this part, the exchange rates of the main exporting countries are imposed on the net convenience yield model as a result of the global trade environment. However, in spite of this, the reference prices for the international market usually are taken from the recognized futures exchange markets. This shows that the exporter does not fully control the price of a commodity: it is determined by the demand, supply and also the market participants. For example, TOCOM and SICOM are the main rubber exchange markets in the world; however, the rubber does not grow in Japan and Singapore. Thailand is the main rubber exporter. In

Table 5.7: The estimations of coffee net convenience yield with Gaussian and Standardised-t error distributions

| | 2nd Contract | | | 4th Contract | | | 6th Contract | | |
|---|---|---|---|---|---|---|---|---|---|
| GARCH | Coefficient | S.E. | t-Statistic | Coefficient | S.E. | t-Statistic | Coefficient | S.E. | t-Statistic |
| $\omega$ | 0.0000 | 0.0000 | 8.2230 | 0.0000 | 0.0000 | 0.0005 | 0.0000 | 0.0000 | 0.5742 |
| $\alpha$ | 0.8768 | 0.0004 | 2128.0173 | 0.0335 | 0.0003 | 111.1040 | 0.8403 | 0.0028 | 301.3750 |
| $\beta_1$ | 0.1132 | 0.0004 | 274.0722 | 0.9565 | 0.0003 | 3795.5941 | 0.1465 | 0.0054 | 26.9736 |
| $\mu$ | 0.0000 | 0.0000 | -3.3664 | 0.0000 | 0.0000 | 45.1383 | 0.0000 | 0.0000 | 0.9256 |
| $\beta_2$ | -0.0084 | 0.0017 | -4.9028 | -0.0176 | 0.0002 | -76.6108 | -0.0052 | 0.0026 | -2.0005 |
| MLE | 44847.0403 | | | 46020.1811 | | | 47084.9558 | | |
| $\omega$ | 0.0000 | 0.0000 | 3.6067 | 0.0000 | 0.0000 | 0.0001 | 0.0000 | 0.0000 | 1.2993 |
| $\alpha$ | 0.7382 | 0.0047 | 155.5818 | 0.0110 | 0.0001 | 96.1523 | 0.4454 | 0.0003 | 1511.7687 |
| $\beta_1$ | 0.2510 | 0.0005 | 511.2264 | 0.9890 | 0.0001 | 8733.1136 | 0.5243 | 0.0006 | 850.6407 |
| $\mu$ | 0.0000 | 0.0000 | -25.1510 | 0.0000 | 0.0000 | -34.0211 | 0.0000 | 0.0000 | -15.3931 |
| $\beta_2$ | 0.0055 | 0.0008 | 7.2633 | 0.0009 | 0.0000 | 54727.3106 | -0.0022 | 0.0004 | -6.3021 |
| $\nu$ | 2.8555 | 0.0015 | 1919.8993 | 2.4232 | 0.0013 | 1914.9103 | 2.8303 | 0.0022 | 1281.3236 |
| MLE | 46227.7536 | | | 48100.6974 | | | 48825.3856 | | |
| Likelihood Ratio test | 2761.4266 | | | 4161.0326 | | | 3480.8596 | | |
| IGARCH | | | | | | | | | |
| $\omega$ | 0.0000 | 0.0000 | 2.7988 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.6580 |
| $\beta_1$ | 0.4580 | 0.0003 | 1599.1783 | 0.9813 | 0.0003 | 2858.9820 | 0.6989 | 0.0007 | 1023.6427 |
| $\mu$ | 0.0000 | 0.0000 | -8.7492 | 0.0000 | 0.0000 | 9.4512 | 0.0000 | 0.0000 | 51.7782 |
| $\beta_2$ | -0.0161 | 0.0016 | -10.3440 | -0.0115 | 0.0007 | -17.1253 | -0.0154 | 0.0004 | -41.3014 |
| MLE | 44188.1276 | | | 45710.2189 | | | 46651.7479 | | |
| $\omega$ | 0.0000 | 0.0000 | 3.8458 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.3879 |
| $\beta_1$ | 0.3481 | 0.0030 | 116.3973 | 0.9737 | 0.0021 | 471.4160 | 0.6263 | 0.0016 | 383.6739 |
| $\mu$ | 0.0000 | 0.0000 | -20.8112 | 0.0000 | 0.0000 | -19.5546 | 0.0000 | 0.0000 | -17.1725 |
| $\beta_2$ | 0.0027 | 0.0010 | 2.7230 | -0.0005 | 0.0006 | -0.7793 | -0.0023 | 0.0004 | -6.2745 |
| $\nu$ | 2.6619 | 0.0048 | 556.8671 | 2.4565 | 0.0018 | 1360.1610 | 3.4596 | 0.0048 | 719.7845 |
| MLE | 46214.5988 | | | 47995.3693 | | | 48731.7543 | | |
| Likelihood Ratio test | 4052.9424 | | | 4570.3008 | | | 4160.0128 | | |
| Likelihood Ratio test (GARCH and IGARCH) | 26.3096 | | | 210.6562 | | | 187.2626 | | |

addition, the rubber contracts are traded in Japanese Yen and USD at TOCOM and SICOM respectively. Hence, the assumption of exchange rates between exporting countries and the referenced exchange market factor will be investigated.

Rubber, white sugar and raw sugar are examined in this study. As mentioned previously, Thailand is the main rubber exporter. Furthermore, the leading sugar producers are Brazil, the European Union and India. However, India's sugar is mainly traded for domestic consumption. Therefore, the main sugar exporters for our study are Brazil, the Europe Union (EU) and Thailand. The main hypothesis of this part is that the exporting country's exchange rate for the trading currency has a significant effect on the net convenience yield.

The exchange rate system is a factor for consideration as it causes different time intervals in testing. Thailand used a fixed exchange rate until 17 July 1997, after which a managed floating system was introduced. We avoid the problem of the beginning period of the exchange rate system change; hence, the Thai Baht to Yen (Thai Baht/Yen) exchange rate is collected from 1998 to 2010. This time period has been used for Brazil Real to USD (Brazil Real/USD), and Thai Baht to USD (Thai Baht/USD) exchange rate. However, the euro currency was firstly introduced on 1 January 1999; therefore, the Euro to USD (Euro/USD) exchange rate is collected from 2000 to 2010.

The currency exchange equation is as follows

$$NCY_t = \alpha + (1 + \beta_2)NCY_{t-1} + \beta_3 \triangle FX_{t-1} \tag{5.31}$$

The hypothesis of this test is

$$\begin{aligned} H_0 &: \beta_3 = 0 \\ H_a &: \beta_3 \neq 0 \end{aligned}$$

The equation 5.31 is an extension from the net convenience yield modelling study by adding the change in exchange rate variable. A depreciation of the exporting country's currency is employed, for instance, if 30 Baht is equal to 1 USD at t, it will be a positive change when there is a depreciation in Thai Baht, such that it is 40 Baht per USD at t+1. However, there is a concern that interest rate drives both the net convenience yield and the currency exchange

rate variables. Hence, the interest rate will work as a control variable for the equation 5.31 in the analysis in order to prevent misleading results.

$$NCY_t = \alpha + (1 + \beta_2)NCY_{t-1} + \beta_3 \triangle FX_{t-1} + \beta_4 \triangle I_{t-1}, \tag{5.32}$$

All estimations are shown in the Tables B.7 to B.13. For the rubber futures contract analysis in Table B.7, the calibrations of GARCH and IGARCH of the normal distribution and Standardised-t distribution are presented by $\omega$, $\alpha$ , $\beta_1$ and $v$. The constant variables of volatility processes are insignificant, but the other variables of volatility process are significant.

The exchange rate depreciation is $\beta_3$. They are all significant for all types of rubber future contracts, and they have a negative coefficient. This indicates that the exporter does not obtain any benefits from holding the physical agricultural commodity when the exchange rate depreciation occurs. The exchange rate depreciation would generate a higher revenue for the exporter because they convert their inflow from Japanese Yen or USD to a higher total revenue in Thai Baht. If this finding is true, the exporter should prefer to export their products to the world market. If demand remains unchanged, then the lower equilibrium and the higher quantity have been discovered.

The risk free rate of Japan is used in this equation because the quote price of a rubber futures contract in TOCOM is in Japanese Yen. If the exporter employs these prices as the reference price, they will convert from Japanese Yen to their currency. Therefore, the interest rate related to the quoted price in a futures contract is exercised. The coefficient of the interest rate variable $\beta_4$ that is assumed to be a control variable is insignificant except for in the second contract with a Standardised-t error distribution estimation. The likelihood ratio test also indicates that the GARCH (1,1) with Standardised-t error distribution is outperformed, which is similar to the previous modelling study.

Moreover, the explanation for this decreasing price is apparently described by the standard futures formula. The net convenience yield is the deducting variable from the standard futures formula. If there is a depreciation of the exporting country's currency, for instance, the previous net convenience yield is 10 at $t = 0$, then the net convenience is decreased to 5 at $t = 1$ as

a result of the exchange rate depreciation. The futures price is then likely to decrease. This clarification is true only when the net convenience yield is positive.

$$F_t = S_0 \exp^{(r-NCY_{t,T})}$$

This explanation corresponds well to the demand and supply conditions that represent the decreasing futures price when there is an increasing supply in the market shown in Figure 5.9. The x-axis and y-axis represent a quantity ($Q$) and a price ($P$) of the product. The equilibrium ($E$) point is discovered where the quantity of demand ($D$) equal to the quantity of supply ($S$). In our case, when the increasing supply and the demand unchanged that occurs in the market. The new supply curve ($S'$) is found. This causes to the new equilibrium point ($E'$) while shows a lower price when there is a higher supply.

Figure 5.9: Demand and Supply curves

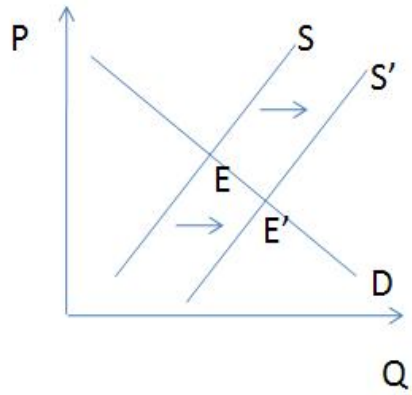



Table B.8 to B.10 illustrate the calibrations of white sugar (LIFFE) with Thai Baht, Brazil Real and the Euro to USD. There are some interesting results for white sugar. The background of the international market shows that Brazil intensively exports raw sugar. On the other hand, European countries exclusively export white sugar. The calibrations show that mixed signs of Thai Baht/USD and Real/USD are found in both GARCH and IGARCH, so the assumption that the exchange rate of Thailand and Brazil effects the net convenience yield in white sugar should not be accepted. However, the negative coefficients of the Euro/USD are estimated for different times to maturity. The consistent appearance of negative coefficients represents

the depreciation of Euro/USD and causes a decrease in net convenience yield for exporters in Europe. The GARCH (1,1) with Standardised-t error distribution is an optimal option for calibration.

Raw sugar is last to be tested in this part. The estimations are presented in the Tables B.11 to B.13. Firstly, the negative coefficients of Brazil Real/USD with GARCH and IGARCH have been discovered in the NYBOT. These estimations indicate that the depreciation of Brazil Real/USD is diminishing the benefit of a Brazilian exporter physically holding an agricultural commodity. Positive and negative coefficients have been found in Table B.11, so there are no consistent patterns of exchange rate between the raw sugar net convenience yield and Thai Baht. Both negative and positive coefficients have been discovered in the Euro/USD exchange rate as well. As we know that the European exporter produces only white sugar, they do not have to contend with the weather conditions necessary for raw sugar. Therefore, these findings meet our expectations.

## 5.5 Conclusion

This chapter aims to examine the net convenience yield behaviour of seven agricultural commodities futures contracts. The net convenience yield is directly calculated by backwardation method from the futures contract prices. The net convenience yield term structure is plotted. A key finding is that the net convenience yield is an important element in short term pricing, but it vanishes for the long term futures pricing process. Moreover, the observations of the net convenience yield strongly demonstrate the fat-tail distributions and heteroskedasticity. The existing heteroskedasticity tests and the mixed test are demonstrated. Heteroskedasticity in all samples are detected.

The autoregressive (AR (1)) process is constructed as net convenience yield modelling. While heteroscadasiticity exists, we use the maximum likelihood estimation (MLE) procedure. Two- time varying volatility, GARCH (1,1) and IGARCH (1,1), is assumed. Furthermore, Gaussian and Standardised-t distribution are used to compare the ability to capture fat-tailed

behaviour. The empirical results show that the GARCH (1,1) with Standardised-t distribution outperforms.

In addition, this chapter focuses on the leading exporting countries of sugar and rubber for the international market, and the exchange rate of Thai Baht against Japanese Yen, and Thai Baht, the Euro and the Brazil Real against the USD are included in the net convenience yield modelling. The results strongly indicate that the depreciation of the leading exporting country's currency reduces the benefit of holding the physical agricultural commodity. Future research should investigate the effects of the exchange rate on the different futures markets with various commodities because there are distinctive features among agriculture exporters.

# Chapter 6

# Rainfall Modelling and Insurance Pricing with Hybrid Distribution

## 6.1 Introduction

Weather is an important factor for many kinds of business, such as energy, tourism, transportation and agriculture. Adverse weather events in recent years, for example, Hurricane Katrina in the USA in 2005, or the major flooding in Thailand in 2011, were two of the costliest natural disasters in the world. These events caused an enormous amount of damage to businesses, to lives and to properties: the overall losses were 125,000 million US$ and 40,000 million US$ respectively (Munich Re NatCatSERVICE®). In light of the magnitude of the costs, businesses potentially exposed to such natural disasters should consider how to manage risk. Weather insurance would be an effective tool for managing weather risk. Weather risks for agriculture include droughts, floods, windstorms or tornadoes. This chapter focuses on rainfall risk.

Weather derivatives are becoming increasingly available. The first standardised contract was traded on the Chicago Mercantile Exchange (CME) in September 1999 and was based on Cooling Degree Days (CDD) and Heating Degree Days (HDD). The most recently weather based derivative is a rainfall derivative which was first traded in 2010.

Rainfall modelling for weather index insurance is a relatively new area of research. The relevant characteristics of rainfall are that it is a non-negative variable, and that extremely high

or extremely low rainfall results in disaster. Modelling these characteristics for a particular area and combining the modelling with the pricing approach in rainfall index insurance will benefit the insurer and the farmer exposed to weather risk.

Section 6.2 of this chapter reviews scholarly research papers in this area. Section 6.3 analyses the rainfall data and attempts to represent seasonality and extreme events. A hybrid probability distribution is proposed and explained. Sections 6.4 and 6.5 demonstrate rainfall weather derivative pricing and gives numerical applications of rainfall index insurance using Monte Carlo methods. Finally, the conclusion and remarks on the findings are presented in Section 6.6.

## 6.2 Literature Review

Weather derivatives and insurance are widely employed in order to manage risk. For example, ski resorts require a certain amount of snow: too little or too much results in a significance loss. Ski resorts can protect themselves from weather risk by buying weather derivatives. Relevant weather risks may include temperature, snow, rain storm, and hail storm (Hull, 2008).

Many research papers on the benefits of using weather derivatives have been published in the last few decades, and their results have been applied to many businesses. In this chapter, we concentrate on agriculture. Skees et al. (2001) claim that rainfall index insurance is beneficial to the farmer in reducing the weather risk and is an objective form of insurance as the payment relies on rainfall measurements from a weather station. A study of drought insurance in Morocco is introduced and the coefficient of variation (CV) of yields is the measure of relative risk. A CV comparison between no insurance, a 5 per cent payment rate insurance contract and a 10 per cent payment rate insurance contract show that the relative risk of a 10 per cent contract portfolio is significantly lower than both the 5 per cent insurance contract and no contract at all. Finally, they suggest that Morocco should establish a pilot drought insurance programme in different agro-climate zones in order to make insurance attractive to

both farmers and insurance companies.

Hazell and Hess (2010) claim that drought insurance is an important instrument that helps the food industry in dry land areas of developing countries to manage their weather risk. Unfortunately, their findings indicate that the premium is relatively high for the farmer, and there is a shortage of infrastructure for a reliable weather measurement. Thus, government support would be required. Chantarat et al. (2007) points out that rainfall index insurance improves the quality of life for livestock farmers in North Kenya. The weather insurers' instantaneous financial response to an emergency event is the main advantage for increasing famine prevention. A simple insurance contract, with cumulative rainfall over the high and low seasons compared with the specified threshold, is demonstrated; this is an attractive contract because it increases the trading chances of the reinsurance market. Furthermore, the entitled region insurance contract seems less costly than then location separate contract.

Nieto (2010) suggests that smallholder farmers can improve their financial performance by using weather insurance to manage drought risk. Alternative specifications for rainfall derivatives are investigated: site-specific and soil-specific rainfall insurance. In addition, Manfredo and Richards (2009) claim that basis risks, such as production risk and price risk in agriculture, can be hedged by using weather insurance; however, insufficient attention to specified locations and the relationship between weather and a production (volumetric risk) causes to an inefficient hedging approach and liquidity problems. Manfredo and Richards chose Fresno County, central California, for their study. They found that both high and low temperatures would adversely affect agricultural production. The relationship between weather and production should be assumed as nonlinear, as such, provisions should be made for a more realistic pricing for weather insurance in managing basic risk. Non-linear payoffs (a straddle position) for low degree days outperform hedging for a non-linear volume-weather relationship risk. On the other hand, Turvey and Chantarat (2006) claim that the use of weather derivatives does not clearly represent financial activities, such as loan repayments. They suggest that key elements for pricing a weather-based financial instrument is a probability distribution of weather variables and the quality of weather data used.

Turvey (2001) claims that the weather-based instrument provides a hedge against production (volumetric risk) rather than price risk in agriculture. Firstly, the relationship of weather and production for corn, soybeans and hay is studied assuming a Cobb-Douglas production function. The results indicate a significant relationship between the weather variables, rainfall and temperature, and production. Moreover, he confirms that the specific location is an important concern for hedging accuracy. The numerical calculation of a rainfall and heat-based put option, a call option and an insurance premium in Woodstock, Ontario, is shown as an example. The call and put value equation is as follows:

$$V_{call} = \theta \int^{\partial_a} (\partial_a - \partial) f(\partial) d\partial \, for \, \partial < \partial_a \tag{6.1}$$

$$V_{put} = \theta \int_{\partial_b} (\partial - \partial_b) f(\partial) d\partial \, for \, \partial > \partial_b \tag{6.2}$$

where f($\partial$) is a probability distribution function using the historical observation to predict the current risk. For a rainfall derivative, the two types of relevant strike price are the high rainfall level (flooding) and the low rainfall level (drought). The premium of the higher strike price is more expensive than the lower strike level.

Even though there are many significant advantages in using weather derivatives, weather derivative pricing does not seem to be a popular topic, as there are few papers on weather derivative and insurance pricing. The popular option pricing model, the Black-Scholes model, cannot be used for calculating weather risk because weather variable is non-tradable. The existing research on weather derivatives and insurance pricing has been studied: Turvey et al. (2006) proposes a weather insurance pricing model with random strike prices for the ice-wine industry in Ontario using Monte Carlo methods to estimate the insurance premium. A random strike price depends on the last month's harvest hours. A normative expected utility model is used as the wine firm's utility function. The risk for the ice-wine industry is that limited harvesting time in may adversely affect revenues over the winter period if enough grapes are not harvested. Fair premiums with constant and random strike levels are calculated. The

results indicate that the insurance premium does not only depend on the required harvest hours but also on the farm location. Finally, they suggest that identical hedging and pricing methods are required for each agricultural product.

Alaton et al. (2002) develops a pricing model for temperature derivatives. A seasonal stochastic process of temperature is introduced; the temperature records of Sweden over the last 40 years are employed in the temperature modelling. As the stochastic model is used, a monthly variance is assumed to capture the variation in each month, and also the mean reversion of temperature is assumed in their research. The heating degree-day option at Bromma Airport is an example estimated by an option formula and by Monte Carlo methods. The empirical results from three different strike price contracts show superior performances when the call options are in-the-money options. In addition, the empirical results show that the premium relies on the location index and the strike price, similar to the findings of Turvey (1999).

For a rainfall modelling, Sanso and Guenni (1999) model rainfall in the Venezuelan state of Guarico over a fixed period. The probability of rain occurrence is determined by the truncated normal model and the rainfall amount using the dynamic linear model. The estimation session uses a Markov chain Monte Carlo methods (MCMC). The two-state rainfall modelling has been studied by Wilks (1998). This model consists of the state of rainfall occurrence and rainfall amount estimated by a mixed exponential distribution. They found that the estimation of the mixed exponential distribution is better than a gamma distribution. This finding is similar to the work of Cao et al. (2004). They propose a single-site model that comprises a first order Markov chain for rainfall occurrence, the estimated density function- a gamma distribution and a mixed exponential distribution for the rainfall amount at Chicago Midway Airport. The parameters of these models are estimated by maximum likelihood. Furthermore, the seasonality is modelled by a trigonometric function in the first order Markov chain probability and a mean conditional precipitation. The most recent method used in this study is kernel density estimation. The outcomes of the three methods are compared. The parameters from these calibrations and the put option pricing show that the gamma distribution is less accurate

than the mixed exponential distribution or kernel distribution.

Musshoff et al. (2007) compare three rainfall models: Burn analysis model (non-parametric), index value simulation and their proposed model. The proposed model consists of probability function rainfall density estimated by a mixed exponential distribution and a de-correlation function that explains the effects of the distance between the weather station and the field of production. This model combines a seasonal rainfall, a link between rainy and dry days as an autoregressive model, and a seasonal rainfall density. The fair price rainfall put and call option valuation, in regards to excess rainfall and drought risk, is demonstrated in this study. The proposed model provides lower standard deviations for both option prices. They also show that remote farms must pay a higher premium than farms closer to the weather station.

There is a further study of Musshoff et al. (2011) which determined the risk reduction of using the rainfall option for farmers in Brandenburg, northern Germany. The main objective of this recent study was to include two basic risks into the production framework: a local risk and a geographical risk. The local basic risk is the relationship between the rainfall and wheat yield; the geographic basic risk is a deterministic relationship between the index weather station and the field location. They demonstrate that the best fit for the rainfall sum index and rainfall deficit index are a lognormal distribution and a Weibull distribution, respectively. They compared the revenue of six scenarios: with/without a rainfall option, without both basic risks, without local basic risk but with geographic basic risk, and with both basic risks. The results indicate that in the scenarios without both a local and a geographical basic risk scenario, farmers were provided with a perfectly good hedge. However, when basic risks are taken into account, the hedging effectiveness is almost eliminated. Therefore, these basic risks have an anomalous effect on the hedging performance of rainfall options.

Unexpected, very high rainfall is possibly related to climate change. Agricultural production and the growing process cannot be immediately adapted to avoid damage from irregular seasons. Extreme value theory (EVT) has been applied in many fields, such as the stock market, and is a relevant tool in capturing a rare event. For example, Broussard and Booth (1998) consider rare events in intraday German stock index futures (FDAX) contract prices.

Type II (Frechet) extreme value distribution is found to be a suitable distribution for explaining the intraday FDAX future contract price behaviour, and their finding is used to establish a market's margin requirement. We have found no example of weather derivative valuation using extreme value theory. This chapter will attempt to fill in the gap by considering rainfall modelling in the context of the extreme value theory.

## 6.3 Data and Methodology

### 6.3.1 Data

There are four daily data series running from the beginning of 1998 to the end of 2011 collected from the Thai meteorological department. Four weather stations have been chosen because they are in the largest province of relevant agricultural productions. For example, Ubon Ratchathani is the main city of rice production in Thailand; in 2011, the overall production from this city was approximately 40% of Thailand's total rice production (Thai Rice Association). Kranchanaburi is the largest area for sugar cane production. There was some difficulty in collecting data from the largest rubber production area, which is Suratthani; therefore, the rainfall level from Nakron Srithumarat and Songkla have been used in this research, as these areas are the second largest for rubber production and are also in close proximity to the largest area.

Tables 6.1 and 6.2 illustrate the statistical summary of daily rainfall (for all data) and only positive rainfall (only rainy days). In Table 6.1, the statistics from Nakron Si Thammarat and Songkla, which are located in southern Thailand, are higher than Ubon Ratchathani and Kranchanaburi, which are located in north-eastern and western Thailand respectively. There are two seasons in southern Thailand, summer and rainy seasons, although the other parts of Thailand have three seasons, summer, rainy and winter. Very high excess kurtosis indicates a heavy tail.

As previously mentioned, the data has been separated into two groups: no-rain days and

Table 6.1: Statistic description for daily rainfall level (Millimetres)

| Weather Station | Ubon Ratchathani | Kranchanaburi | Nakron Si Thammarat | Songkla |
|---|---|---|---|---|
| Mean | 4.41 | 2.97 | 7.34 | 6.11 |
| S.D. | 12.65 | 9.79 | 20.60 | 18.78 |
| Skewness | 4.83 | 5.87 | 7.09 | 9.61 |
| Excess Kurtosis | 31.06 | 46.47 | 80.13 | 174.19 |
| Max | 153.00 | 132.40 | 384.50 | 521.80 |
| Min | 0.00 | 0.00 | 0.00 | 0.00 |
| | | | | |
| Rain | 31.78% | 30.04% | 46.96% | 43.87% |
| No-Rain | 68.22% | 69.96% | 53.04% | 56.13% |
| Total observations | 5113 | 5113 | 5113 | 5113 |

rainy days. In Table 6.2, high excess kurtosis still presents, especially in the total positive and top dataset. We separated the positive rainfall data into heavy and middle groups according to the extreme value theory for composing hybrid distribution.

Figure 6.1 show the daily rainfall level over 1998 and 2011. All weather stations clearly demonstrate seasonality, as 14 cycle movements are drawn over the 14 years sample. The dashed red line represent the 95 percentile of possitive rainfall that is used in the rainfall modelling. Figure 6.2 shows the heavy rainfall group that demonstrate no seasonal pattern, but it clearly see the seasonal pattern in the moderate rainfall group in Figure 6.1. Figure 6.3 represents a histogram of rainfall, showing the high frequency of zero or close to zero rainfall. Figure 6.4 exhibits the rainfall level excluding dry days. These four pictures represent the high frequency of close to zero rainfall, and it is compared with a fitted normal distribution. Figure 6.5 is the smooth density of positive rainfall pictures, which are drawn from the kernel smoothing density estimate function in MATLAB. These provide a guide to the optimal shape of the probability density function.

### 6.3.2 Methodology

In the rainfall modelling, we consider a two-step approach. The two-step approach initially starts with the unconditional probability rainfall estimation. Rainfall level is calculated in the

Table 6.2: Statistic description for positive rainfall level(Millimetres)

| **Weather Station** | **Ubon Ratchathani** | **Kranchanaburi** | **Nakron Si Thammarat** | **Songkla** |
|---|---|---|---|---|
| Mean | 13.87 | 9.90 | 15.63 | 13.92 |
| S.D. | 19.29 | 15.84 | 27.83 | 26.37 |
| Skewness | 2.72 | 3.25 | 5.23 | 7.02 |
| Excess Kurtosis | 9.98 | 14.27 | 43.47 | 92.22 |
| Top (Higher than 95 percentile) | | | | |
| Mean | 59.92 | 48.40 | 78.46 | 71.20 |
| S.D. | 24.02 | 21.73 | 50.92 | 51.24 |
| Skewness | 1.62 | 1.90 | 3.11 | 4.90 |
| Excess Kurtosis | 2.61 | 3.65 | 12.36 | 33.81 |
| Middle (Lower than or equal to 95 percentile) | | | | |
| Mean | 8.74 | 5.61 | 8.64 | 7.54 |
| S.D. | 9.31 | 6.54 | 9.41 | 8.64 |
| Skewness | 1.21 | 1.46 | 1.40 | 1.48 |
| Excess Kurtosis | 0.49 | 1.21 | 1.22 | 1.41 |
| | | | | |
| Max | 153.00 | 132.40 | 384.50 | 521.80 |
| Min | 0.10 | 0.10 | 0.10 | 0.10 |
| Total observations | 1625 | 1536 | 2401 | 2243 |

Figure 6.1: The daily rainfall level plots of all weather stations

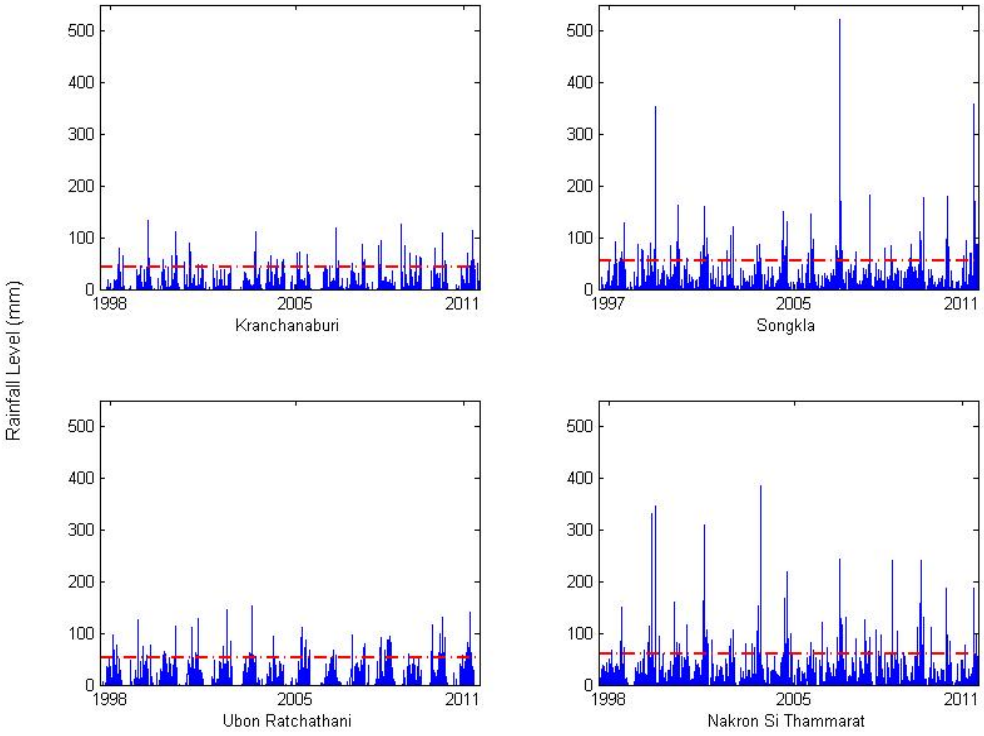


Figure 6.2: The daily heavy rainfall conditional level plots of all weather stations

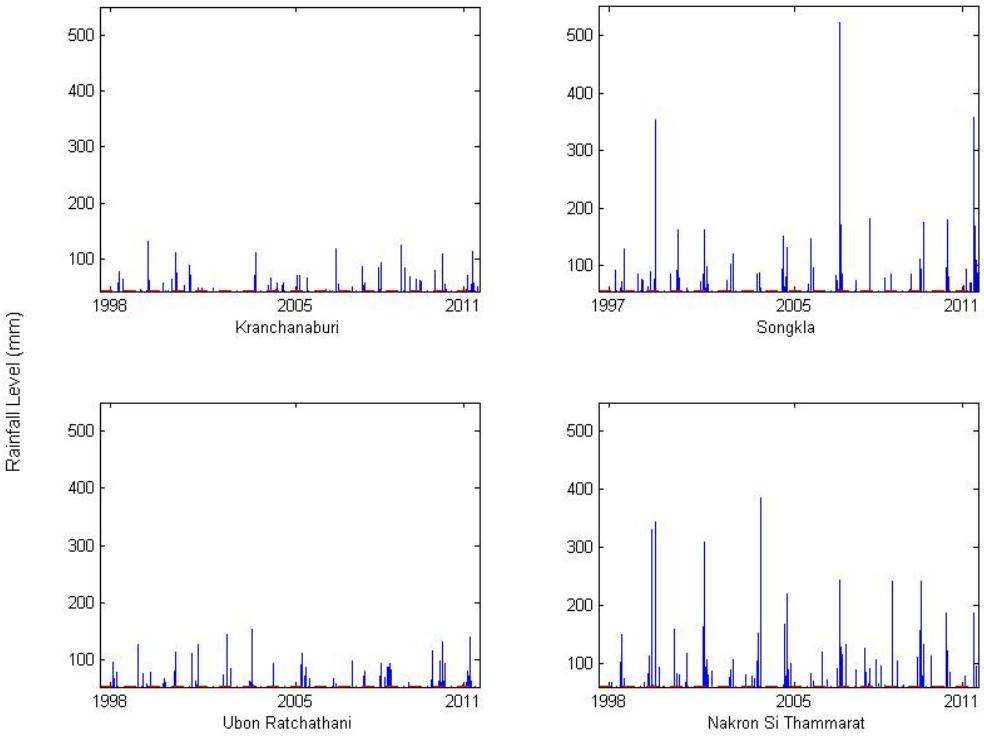


Figure 6.3: Histrogram of rainfall level of all weather stations

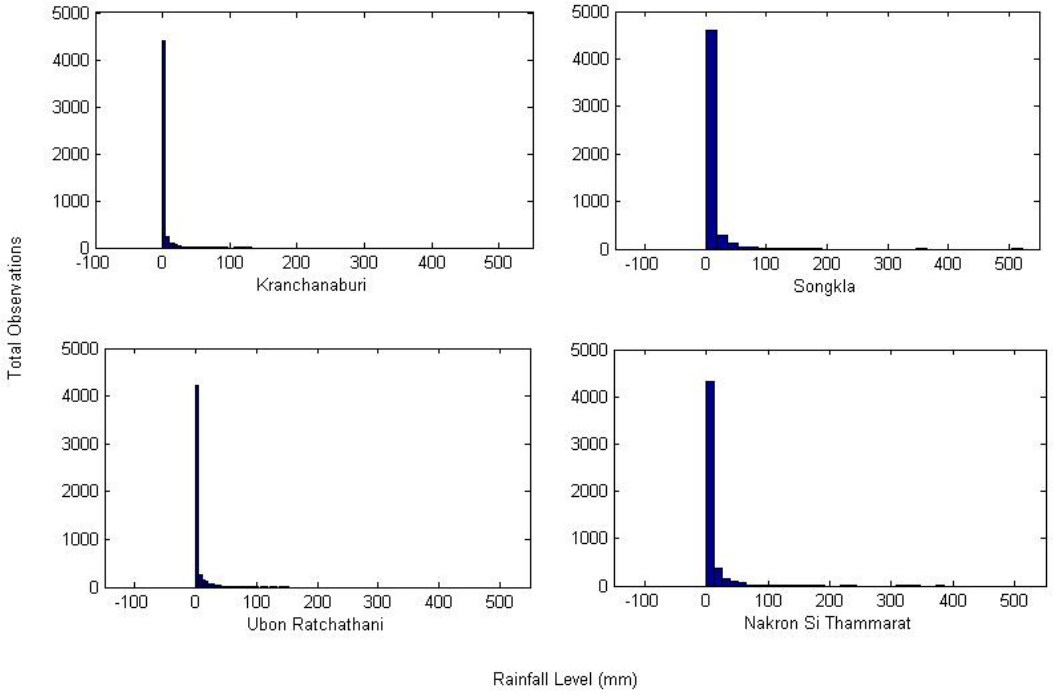


Figure 6.4: Histrogram of positive rainfall level and the normal distribution curve of all weather stations

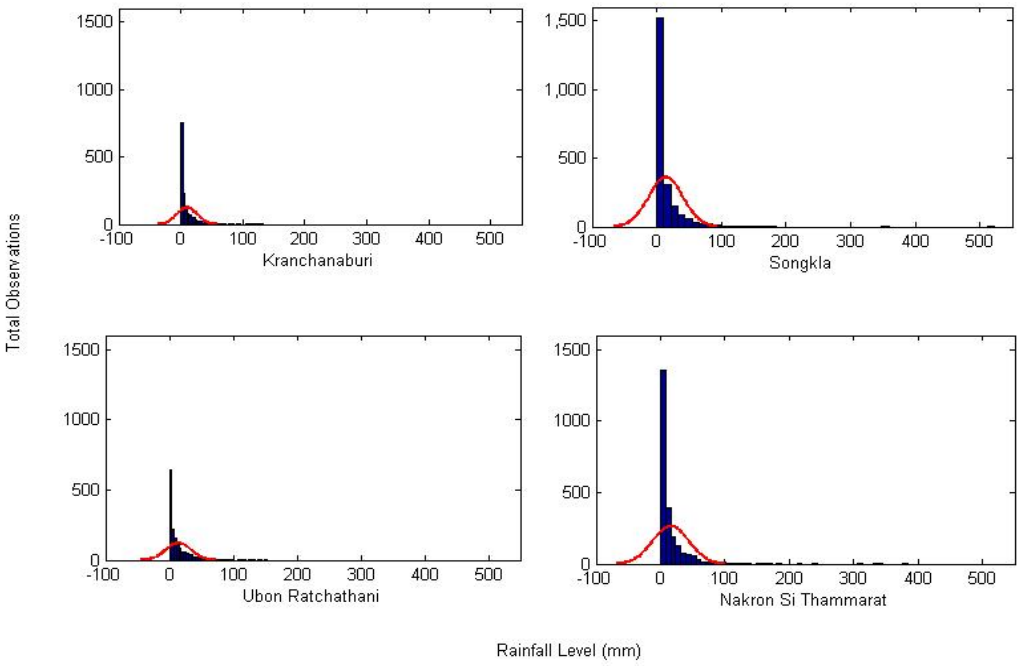
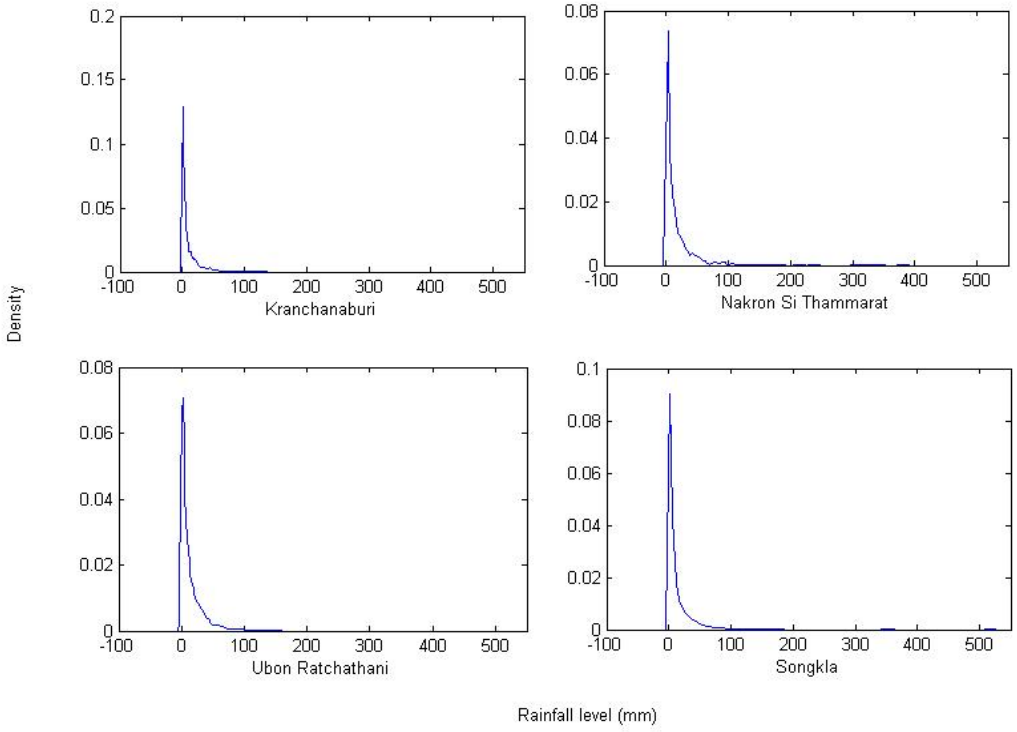


Figure 6.5: Kernel density estimation of all weather stations



second step approach. The proposed density function must take two significant characteristics that are high kurtosis and non-negative value into account. The rainfall data is primitively grouped to dry-day and rainy day before using the peak over threshold to categorise the positive rainfall in density estimation approach. Moreover, the unexpected high rainfall level, such as storm and hurricane, and seasonal pattern must be included to provide a more realised model. Trigonometric variables are incorporated in both the unconditional probability and rainfall density estimations. The explanation follows.

#### 6.3.2.1 Rain Occurrence

Firstly, we assume $I_{U,t}$ that is the random variable indicating rain occurrence;

$$I_{U,t} = \begin{cases} 0 & if\ day\ t\ is\ no-rain \\ 1 & if\ day\ t\ is\ rain \end{cases} \tag{6.3}$$

As mentioned in early discussion, the seasonality exists in the probability function, hence the assumption of seasonality using the trigonometric function introduced by Hanna,Terry and Tuckwell (1970). The seasonal probability is

$$\Pr(Rain) = I_t = \mu + \Sigma_{k=1}^{K^*}\left[\gamma_{p,k}\cos\left(\frac{2\pi kt}{S}\right) + \varphi_{p,k}\sin\left(\frac{2\pi kt}{S}\right)\right] + \varepsilon_t \tag{6.4}$$

$$\Pr(Rain) = I_t = \mu + \Sigma_{k=1}^{K^*}\left[\gamma_{p,k}\cos\left(\frac{2\pi kt}{366}\right) + \varphi_{p,k}\sin\left(\frac{2\pi kt}{366}\right)\right] + \varepsilon_t \tag{6.5}$$

where $\mu_t$ is a time varying mean and $S$=366 days is the number of days in a year. Therefore, the probability of rain occurrence is a function of the seasonality which is represented by the cosine and sin function.

#### 6.3.2.2 Rainfall Intensity Estimation

For rainfall intensity estimation, the positive rainfall is managed to be two datasets according to the peak over threshold. The data that over the certain threshold would be calculated with the extreme value distribution, on the other hand, the data that below the threshold (T) is estimated with the Weibull error distribution. The 95 percentile of the distribution of positive rainfall is used as a threshold (T).

$$X_t = 0 \quad if\, x_t = 0$$

$$X_{M,t} = x_t \quad if\, x_t \leq T$$

$$X_{H,t} = x_t \quad if\, x_t > T$$

The rainfall level is assumed as

$$x_t = \mu + \varepsilon_t \tag{6.6}$$

As we employ the maximum likelihood estimation, the error distribution needs to be explained. The lower threshold is called a moderate rainfall level; we employ Weibull error distribution because it is generally used for non-negative variable and also found in some weather research, such as wind speed estimation by Seguro and Lambert (2000). Two parameter of Weibull probability density distribution are

$$f\left(x_t \mid \sigma_W, \xi_W\right) = \frac{\xi_W}{\sigma_W}\left(\frac{x_t}{\sigma_W}\right)^{\xi_W - 1} \exp\left\{-\left(\frac{x_t}{\sigma_W}\right)^{\xi_W}\right\} \tag{6.7}$$

The cumulative density function is$1-\exp-\left(\frac{x}{\sigma_w}\right)^{\xi_w}$and the mean is $\sigma_w\Gamma\left(1+\frac{1}{\xi_w}\right)$. Once the seasonality components have been introduced into the Weibull error distribution, the seasonal scale ($\sigma$) of Weibull error distribution is

$$\sigma_W = \sigma_{WS} + \Sigma_{k=1}^{K^*}\left[\gamma_{WS,k}\cos\left(\frac{2\pi kt}{366}\right) + \varphi_{WS,k}\sin\left(\frac{2\pi kt}{366}\right)\right] \tag{6.8}$$

Extreme value distribution is divided into 3 types of error distributions, namely Gumbel-type Distribution (type I), Frechet-type distribution (type II) and Weibull distribution (type III).

However, these three different error distributions can be written in the form of the generalized extreme value (GEV) distributions with cumulative distribution function as

Probability Density function (PDF):

$$f\left(x_t \mid \mu_G, \sigma_G, \xi_G\right) = \left\{\exp - \left\{\left(1+\xi_G \frac{(x_t-\mu_G)}{\sigma_G}\right)^{-\frac{1}{\xi_G}}\right\}\right\} \frac{1}{\sigma_G}\left(1+\xi_G \frac{(x_t-\mu_G)}{\sigma_G}\right)^{-1-\frac{1}{\xi_G}} \tag{6.9}$$

Cumulative distribution function (CDF) :

$$\Pr\left[X \leq x_t\right] = \exp - \left[1+\xi_G\left(\frac{x_t-\mu_G}{\sigma_G}\right)\right]^{-1/\xi_G} \tag{6.10}$$

for $1+\xi\left(\frac{x_t-\mu}{\sigma}\right) > 0$

The mean of the generalised extreme value distribution is

$$\mu_G + \sigma_G \frac{\Gamma\left(1-\xi_G\right)-1}{\xi_G}$$

and we will use the maximum log-likelihood to estimate the parameters. From the estimation of generalized extreme value estimation, three possible optimal functions explain the sample style. If $\xi$>0, the distribution is approaching to Frechet distribution (Type II), on the other hand, if $\xi$<0, the sample distribution is Weibull distribution (Type III). The Gumbel distribution seem suitable for the sample when $\xi$=0. These three distributions have the probability function and cumulative distribution functions are following

**Gumbel-type Distribution (type I)**

Probability Density function (PDF):

$$f\left(x_t \mid \mu, \sigma\right) = \frac{1}{\sigma}\exp - \left(\frac{x_t-\mu}{\sigma}\right)\exp\left(-\exp\left(-\left(\frac{x_t-\mu}{\sigma}\right)\right)\right) \tag{6.11}$$

Cumulative distribution function (CDF) :

$$F\left(x\right) = \Pr\left[X \leq x_t\right] = 1 - \exp\left[-\exp^{(x_t-\mu)/\sigma}\right] \tag{6.12}$$

**Frechet-type distribution (type II)**

Probability Density function (PDF):

$$\begin{aligned} f\left(x_t \mid \mu, \sigma, \xi\right) &= -\left(\frac{x_t-\mu}{\sigma}\right)^{-\xi-2} \xi^2 \exp\left(-\left(\frac{x_t-\mu}{\sigma}\right)^{-\xi}\right) \\ &\quad -\left(\frac{x_t-\mu}{\sigma}\right)^{-\xi-2} \xi \exp\left(-\left(\frac{x_t-\mu}{\sigma}\right)^{-\xi}\right) \\ &\quad +\left(\frac{x_t-\mu}{\sigma}\right) \xi^2 \exp\left(\left(\frac{x_t-\mu}{\sigma}\right)^{-\xi}\right) \end{aligned} \tag{6.13}$$

Cumulative distribution function (CDF) :

$$F\left(x\right) = \Pr\left[X \leq x_t\right] = \begin{cases} 0 & x_t < \mu \\ \exp\left\{-\left(\frac{x_t-\mu}{\sigma}\right)^{-\xi}\right\} & x_t \geq \mu \end{cases} \tag{6.14}$$

**Weibull distribution (type III)**

Probability Density function (PDF):

$$f\left(x_t \mid \mu, \sigma, \xi\right) = \frac{\xi}{\sigma}\left(\frac{x_t-\mu}{\sigma}\right)^{\xi-1} \exp\left(-\left(\frac{x_t-\mu}{\sigma}\right)^{\xi}\right) \tag{6.15}$$

where $x_t - \mu > 0$, $\beta > 0$,

Cumulative distribution function (CDF) :

$$F\left(x\right) = \Pr\left[X \leq x_t\right] = \begin{cases} \exp\left\{-\left(\frac{x_t-\mu}{\sigma}\right)^{\xi}\right\} & x_t \leq \mu \\ 0 & x_t > \mu \end{cases} \tag{6.16}$$

**The hybrid distribution model**

Now, we create a distribution that is able to represent the data from all three scenarios: dry-day, moderate rainfall and peak events. Firstly, rainfall probability is assumed to be the first step, which is followed by the separation of seasonality probability into dry-day and rainy-day as

$$P\left(Rain\right) = \begin{cases} \left(1 - \Pr\left(Rain\right)\right) & \text{if } x_t = 0 \\ \Pr\left(Rain\right) & \text{if } x_t > 0 \end{cases} \tag{6.17}$$

The second step is rainfall distribution. As rainy day data is separated into high and moderate rain according to the POT criterion, two scenarios emerge. The truncated distributions of data both below and above the threshold are exercised. The moderate rainfall level is modelled by the truncated Weilbull distribution, and the heavy rainfall level is modelled the truncated generalized extreme value distribution. The hybrid rainfall distribution is

$$\phi_R(x_t) = \begin{cases} 1 - \Pr\left(Rain\right) & x_t = 0 \\ 0.95 \times \Pr\left(Rain\right) & \text{if } x_t \leq \rho_{0.95} \\ \times \frac{\phi_{weibull}(x_{M,t}|\xi_w,\sigma_w)}{\Phi_{weibull}(x_{\rho_{0.95}}|\xi_w,\sigma_w) - \Phi_{weibull}(x_{x=0}|\xi_w,\sigma_w)} & \\ 0.05 \times \Pr\left(Rain\right) & \text{if } x_t > \rho_{0.95} \\ \times \frac{\phi_{GEV}(x_{H,t}|\xi_G,\sigma_G,\mu_G)}{\Phi_{GEV}(x_{\infty}|\xi_w,\sigma_w) - \Phi_{GEV}(x_{\rho_{0.95}}|\xi_G,\sigma_G,\mu_G)} & \end{cases} \tag{6.18}$$

Moreover, the link between the truncated Weilbull distribution and the truncated generalized extreme value distribution should be considered because of the smoothness of the condition. Hence, the distribution of the threshold must satisfy a smooth condition which is

$$\Phi_{R|weibull}(x_{\rho_{0.95}}) = \Phi_{R|GEV}(x_{\rho_{0.95}}) \tag{6.19}$$

Other conditions, such as the total probability distribution function of rainfall hybrid distribution, must be equal to one, so

$$\phi_{weibull}(x \mid 0 < x < x_{\rho=0.95}) + \phi_{GEV}(x \mid x > x_{\rho=0.95}) = 1$$

and the probability distribution function of truncated Weibull distribution at $x = 0$ is zero,

$$\Phi_{weibull}(x_{x=0} \mid \xi_w, \sigma_w) = 0$$

The following three statements express the simple probability distribution function of rain-

fall hybrid distribution:

$$\phi(x_t) = \begin{cases} 1 - \Pr(Rain) & x_t = 0 \\ 0.95 \times \Pr(Rain) \times \frac{\phi_{weibull}(x_{M,t}|\xi_w,\sigma_w)}{\Phi_{weibull}(x_{\rho_{0.95}}|\xi_w,\sigma_w)} & \text{if } x_t \leq \rho_{0.95} \\ 0.05 \times \Pr(Rain) \times \frac{\phi_{GEV}(x_{H,t}|\xi_G,\sigma_G,\mu_G)}{1-\Phi_{weibull}(x_{\rho_{0.95}}|\xi_w,\sigma_w)} & \text{if } x_t > \rho_{0.95} \end{cases} \tag{6.20}$$

The cumulative distribution function (cdf) of the rainfall function is

$$\Phi_R(x_t) = \int_0^{x_t} Rainfall = \begin{cases} 1 - \Pr(Rain) & \text{if } x_t = 0 \\ [1 - \Pr(Rain)] + \left[0.95 \times \Pr(Rain) \times \frac{\left(1-\exp\left(-\left(\frac{x_t}{\sigma_w}\right)^{\xi_w}\right)\right)}{\Phi_{weibull}(x_{\rho_{0.95}}|\xi_w,\sigma_w)}\right] & \text{if } 0 < x_t \leq \rho_{0.95} \\ [1 - \Pr(Rain)] + \left[0.95 \times \Pr(Rain) \times \frac{\left(1-\exp\left(-\left(\frac{x_t}{\sigma_w}\right)^{\xi_w}\right)\right)}{\Phi_{weibull}(x_{\rho_{0.95}}|\xi_w,\sigma_w)}\right] + \left[0.05 \times \Pr(Rain) \times \frac{\exp -\left[1+\xi\left(\frac{x_t-\mu_G}{\sigma_G}\right)\right]^{-1/\xi_G}}{1-\Phi_{weibull}(x_{\rho_{0.95}}|\xi_w,\sigma_w)}\right] & \text{if } \rho_{0.95} < x_t \end{cases} \tag{6.21}$$

## 6.4 Results and Discussion

The estimations and the rainfall index-insurance applications will both be described in this section. Firstly, the calibrations of the hybrid error distribution are reported as well as the goodness of the rainfall model. Secondly, we aim to demonstrate the benefit of hybrid error distribution in the context of insurance: insurance companies would benefit from estimating a fair index-insurance premium.

### 6.4.1 Rainfall Estimations

The estimated parameters of the composed model are shown in equation 6.20 are represented in Tables 6.3 and 6.4. Firstly, the probability estimations from equation 6.5 are represented in Table 6.3. The optimal harmonic for the trigonometric function is selected by observing common significant variables among four weather stations at 5 percent significant levels. Only 3 harmonics are regarded as an optimal lag for all weather stations. Hence, there are 7 parameters to be estimated. All estimations are significant, and the standard error is in parentheses. These estimations will be carried to the second step. R-square is represented in the last row. Seasonal probability is show to have the greatest performance in Ubon Ratchanthani, but, as can be seen in this model, this is offset by the fact that the $R^2$ is only 8.86 per cent at Nakron Si Thammarat.

The rainfall density function is the second step. Non-seasonality mean and seasonal mean model calibrations from equation 6.20 are shown in the Table 6.4. The seasonal scale parameter of Weibull error distribution in equation 6.8 is used for the seasonal mean model shown in the lower part of Table 6.4. The threshold for hybrid distribution, 95 per cent, is firstly calculated from the historical rainfall. The non-seasonal mean model consists of the shape ($\xi_G$), the scale ($\sigma_G$) ,and location ($\mu_G$) of truncated GEV distribution and the shape ($\xi_W$) and the scale ($\sigma_W$) of truncated Weibull distribution. The shape parameters of truncated GEV distribution are positive, indicating that Frechet distribution (type II) is an optimal distribution. All parameters are significant at 10 per cent significance levels. The standard error and the maximum likelihood from the estimations are provided in parentheses.

The seasonal mean model estimations are represented in the lower portion of Table 6.4. The optimal trigonometric lag is considered by selecting the Akaike Information Criteria (AIC) and the Bayesian information criterion (BIC) for every weather station. The lowest AIC number indicates the optimal lag in the equation. The optimal harmonic for Ubon Ratchathani, Kranchanaburi, Nakron Si Thammarat and Songkla are 1, 3, 2 and 1 respectively. The truncated GEV estimations are similar between the seasonal mean and the non-seasonal mean models. However, the estimation in truncated Weibull is not identical. For example, the shape param-

Table 6.3: The estimations of seasonal probability

| | **Ubon Ratchathani** | **Kranchanaburi** | **Nakron Si Thammarat** | **Songkla** |
|---|---|---|---|---|
| $\mu_t$ | 0.3172 (0.0055) | 0.2998 (0.0057) | 0.4697 (0.0066) | 0.4388 (0.0066) |
| $\gamma_{1,pr}$ | -0.3217 (0.0078) | -0.2421 (0.0082) | 0.0118 (0.0094) | 0.0414 (0.0093) |
| $\varphi_{1,pr}$ | -0.1190 (0.0078) | -0.1278 (0.0082) | -0.1643 (0.0094) | -0.1691 (0.0092) |
| $\gamma_{2,pr}$ | -0.0190 (0.0078) | -0.0447 (0.0082) | 0.0179 (0.0094) | 0.0147 (0.0093) |
| $\varphi_{2,pr}$ | 0.0362 (0.0080) | -0.0022 (-0.27) | -0.1242 (0.0094) | -0.1398 (0.0092) |
| $\gamma_{3,pr}$ | 0.0460 (0.0078) | 0.0178 (2.19) | 0.0331 (0.0094) | -0.0097 (0.0093) |
| $\varphi_{3,pr}$ | 0.0394 (0.0080) | 0.0570 (7.01) | 0.0074 (0.0094) | -0.0311( 0.0092) |
| $R^2$ | 28.33% | 19.11% | 8.86% | 10.40% |

eters ($\xi_W$) of non-seasonal mean model are 0.71, 0.68, 0.74 and 0.69 ,and the shape parameters of seasonal model parateres are very similar for Ubon Ratchathani, Kranchanaburi, Nakron Si Thammarat and Songkla respectively. These four parameters are significant.

Moreover, the scale ($\sigma_{WS}$) of truncated Weibull distribution paramteres of all four weather stations are significant. For the calibrations of the truncated GEV distribution are also singificant and similar estimations in both non-seasonal mean and seasonal models. In addition, the log-likelihood ratio tests indicate that the inclusion of trigonometric parameters offers more reliable models than the non-seasonal mean model. For example, the likelihood ratio test of Ubon Ratchathani is 38.18, which is greater than the critical value at 5.99; therefore, the seasonal mean model, rather than the non-seasonal mean model, is optimal.

## 6.5 Monte Carlo Methods and Rainfall Index-Insurance Premium

### 6.5.1 Monte Carlo Methods

The Monte Carlo simulation technique is used to numerically estimate the rainfall. This data is used for the performance evaluation and insurance premium application. The rainfall level from the simulation is required, hence the inverse cumulative of rainfall hybrid distribution is provided. The inverse cumulative distribution function of rainfall model is

Table 6.4: The rainfall estimations of four weather stations

| | **Ubon Ratchathani** | **Kranchanaburi** | **Nakron Si Thammarat** | **Songkla** |
|---|---|---|---|---|
| Non-Seasonality Mean Model | | | | |
| $\xi_G$ | 0.1039 (0.0415) | 0.3230 (0.0139) | 0.2703 (0.0258) | 0.4151 (0.0739) |
| $\sigma_G$ | 17.3280 (4.8137) | 10.9903 (0.9378) | 27.2761 (0.7460) | 19.2289 (1.3811) |
| $\mu_G$ | 52.7258 (6.7847) | 42.4506 (3.5576) | 59.8026 (2.0027) | 68.2359 (2.9514) |
| $\xi_W$ | 0.7090 (0.0922) | 0.6835 (0.0282) | 0.7472 (0.0041) | 0.6903 (0.0068) |
| $\sigma_W$ | 11.0828 (0.3111) | 6.5593 (0.1214) | 10.4784 (0.0425) | 8.9400 (0.1593) |
| MLE | -8124.25 | -7350.19 | -11913.66 | -10906.53 |
| Seasonality Mean Model | | | | |
| $\xi_G$ | 0.1039 (0.0359) | 0.3230 (0.0341) | 0.2718 (0.1086) | 0.4151 (0.0665) |
| $\sigma_G$ | 17.3273 (3.1635) | 10.9901 (0.3409) | 27.2282 (1.7274) | 19.2289 (1.4144) |
| $\mu_G$ | 52.7284 (6.8006) | 42.4525 (5.2480) | 60.2261 (5.3510) | 68.2361 (2.7931) |
| $\xi_W$ | 0.7128 (0.5540) | 0.6981 (0.1724) | 0.7608 (0.2312) | 0.7036 (0.0195) |
| $\sigma_{WS}$ | 8.7240 (0.2943) | 6.7698 (0.1733) | 3.8825 (0.2190) | 9.1817 (0.1895) |
| $\gamma_{1,WS}$ | -5.7616 (0.1657) | 0.8396 (0.1472) | 4.3041 (0.1530) | 3.9188 (0.2447) |
| $\varphi_{1,WS}$ | 0.2015 (1.3251) | 3.6103 (0.2287) | 2.4981 (0.0845) | -0.6086 (0.0424) |
| $\gamma_{2,WS}$ | | -4.7812 (0.1115) | 0.2385 (0.0913) | |
| $\varphi_{2,WS}$ | | 0.8005 (0.5111) | 1.1863 (0.3920) | |
| $\gamma_{3,WS}$ | | -2.4089 (0.0261) | | |
| $\varphi_{3,WS}$ | | -0.3807 (0.3235) | | |
| AIC | 16224.31 | 14645.15 | 23755.09 | 21750.94 |
| BIC | 16270.09 | 14717.09 | 23813.95 | 21796.72 |
| MLE | -8105.16 | -7311.58 | -11868.54 | -10868.47 |
| Likelihood ratio test | 38.18 | 77.23 | 90.22 | 76.12 |
| Critical Value | 5.99 | 12.59 | 9.49 | 5.99 |

$$\Phi^{-1}(y) = \begin{cases} 0 & \text{if } 0 \le y \le 1 - \Pr(Rain) \\ -\sigma_w \ln(1 - (\frac{1-\exp\left(\frac{-x_{\rho=0.95}}{\sigma_w}\right)^{\xi_w}(\Pr(Rain)+y-1)}{0.95\Pr(Rain)})^{\xi^{-1}}) & \text{if } 1 - \Pr(Rain) < y \le 1 - 0.05\Pr(Rain) \\ \mu_G + \frac{\sigma_G}{\xi_G}[\left(-\ln[\left(\frac{y-1+0.05\Pr(Rain)}{0.05\Pr(Rain)}\right)\exp\left(\frac{-x_{\rho=0.95}}{\sigma_w}\right)^{\xi_w}]^{-\xi_G}\right) - 1] & \text{if 1-0.05Pr}(Rain) < y < 1 \end{cases} \tag{6.22}$$

The simulation section begins after the completed estimation task, so all parameters are estimated from the maximum likelihood estimation. The following step in the insurance application, the determination of the probability of rain, is generated firstly by the uniform distribution. The probability of rain and the rainfall level at 95 percentile are computed from the historical rainfall data. The Monte Carlo method is used to generate the rainfall dataset.

## Backtesting Results

We employ two methods to evaluate prediction performances. The simulated rainfall data from the Monte Carlo methods are employed in this backtesting. Firstly, the cumulative relative frequency data function between the forcasted data from the hybrid model and the actual data are depicted in Figure 6.6. The coincident cumulative relative frequency data function are found for all weather stations. These imply a reliable rainfall model. Secondly, the statistic variables also are given. Table 6.5 illustrates the maximum and expected rainfall of the non-seasonality and seasonality models compared with the actual rainfall. Two expected outcomes from truncated Weibull and truncated generalized extreme value distributions are presented for moderate and heavy rainfall respectively, and results clearly show that the proposed rainfall model is able to predict the comparable rainfall. Both cumulative relative frequency data and the statistic comparisons confirm the good model in forecasting.

Figure 6.6: The cumulative relative frequency data of forecasted rainfall and actual rainfall

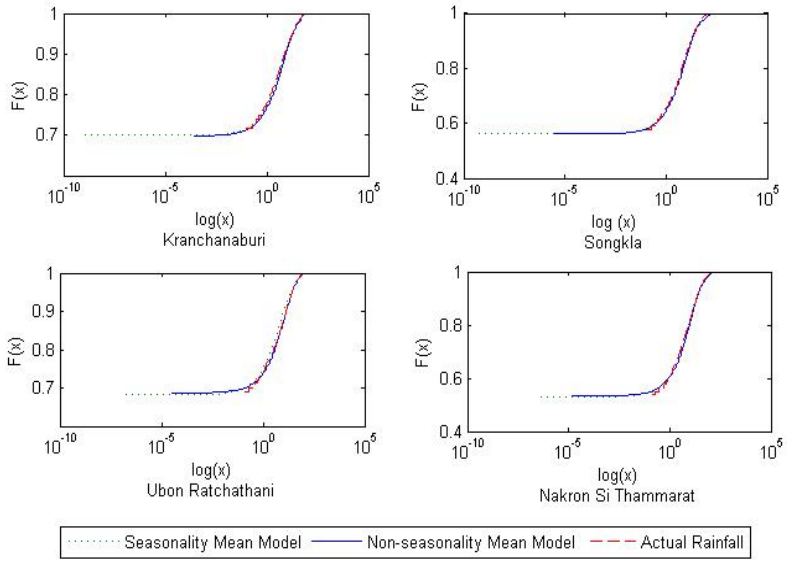



Table 6.5: The maximum rainfall level from the non-seasonality and seasonality mean models (Millimetres)

| | **Ubon Ratchathani** | **Kranchanaburi** | **Nakron Si Thammarat** | **Songkla** |
|---|---|---|---|---|
| **Maximum** | | | | |
| Non-Seasonality Mean Model | 160.36 | 137.87 | 399.03 | 528.92 |
| Seasonality Mean Model | 160.19 | 135.72 | 373.70 | 574.72 |
| Actual Rainfall | 153.00 | 137.45 | 384.50 | 574.72 |
| **Expectation (Truncated Weibull )** | | | | |
| Non-Seasonality Mean Model | 5.21 | 3.23 | 7.58 | 4.66 |
| Seasonality Mean Model | 5.37 | 3.47 | 7.84 | 4.92 |
| Actual Rainfall | 4.40 | 2.95 | 7.33 | 6.10 |
| **Expectation (Truncated GEV)** | | | | |
| Non-Seasonality Mean Model | 13.86 | 8.49 | 12.52 | 11.47 |
| Seasonality Mean Model | 14.41 | 9.33 | 13.08 | 12.36 |
| Actual Rainfall | 13.87 | 9.90 | 15.63 | 13.92 |

### 6.5.2 Rainfall Index-Insurance Premium

This section describes applications of the hybrid distribution model in rainfall index-insurance. An arbitrage free insurance premium means the premium is the total expected cost of ruin (Dickson, 2005).

$$\Pi = \mathrm{E}^{\mathbb{P}}\left[C(x)\right] \tag{6.23}$$

this is called fair premium; however, the insurance company is able to charge their risk premium as

$$\Pi = (1+\theta)\mathbf{E}^{\mathbb{P}}\left[C(x)\right] \tag{6.24}$$

where $\theta$ is an loading factor and $C(x)$ the claim function. In this paper, the rainfall index-insurance is designed for accumulative rainfall over the certain period. The claim is estimated depending on the reference weather station. There are two types of index-insurance: high rain (HR) index-insurance for flooding and low rain (LR) index-insurance for drought. The claim functions for HR and LR rainfall index-insurance are written as

$$C_{HR} = T_{payment} \times (x - A_{HR})^{+} \tag{6.25}$$

$$C_{LR} = T_{payment} \times (x - A_{LR})^{-} \tag{6.26}$$

where $x$ is the accumulative rain over the contract period, $A_{HR}$ and $A_{LR}$ are the strike price of high rain (HR) index-insurance and low rain (LR) index-insurance, which can be a constant and a seasonal variable, and $T_{payment}$ is a triggering indemnity payment. Furthermore, the loading factor is assumed as zero ($\theta = 0$). The index-insurance premium for high rainfall (HR) is

$$\begin{aligned}\Pi_{HR} &= \mathrm{E}^{\mathbb{P}}\left[C(x)\right] \\ &= \int_{A}^{\infty} T_{payment} \times (x-A)^{+} \times \phi_R(x)dx \end{aligned} \tag{6.27}$$

and the index-insurance premium for low rainfall (LR) is

$$\begin{aligned}\Pi_{LR} &= \mathrm{E}^{\mathbb{P}}\left[C(x)\right] \\ &= \int_{\infty}^{A} T_{payment} \times (x-A)^{-} \times \phi_R(x)dx \end{aligned} \tag{6.28}$$

The details of the rainfall index-insurance are as follows. Monthly rainfall index-insurance and 30-days rainfall index-insurance are created as flexible options; moreover, the strike rainfall level can be either constant or seasonal. We estimated the index-insurance premium by using the simulated data from the Monte Carlo method. We studied the main characteristics of compensation and product design from the rainfall futures contract and option traded at Chicago Board of Trade (CBOT), so the triggering indemnity payment for HR and LR rainfall index-insurance that is assumed to be $ 19.6850 per millimetre.

Monthly rainfall index-insurance is designed for the farmers who desire to protect their losses from unexpected weather events over a particular month. They must buy this insurance at the beginning of each month, and the insurance expires at the end of each month. For example, if farmers want to protect their production losses from unpredicted rainfall damage in May, they must buy May's rainfall index-insurance on the 1st of May; furthermore, they have to specify the weather station in the contract, such as Songkla weather station. Compensation will be paid if the rainfall level at the weather station is higher, for HR index-insurance, or lower, for LR index-insurance, than the strike rainfall level.

The expected loss of the insurance firm is 10 per cent of the distribution. The 10 per cent loss exercises for both sides of the distribution. Therefore, the seasonal strike rainfall levels for HR and LR index-insurance are 90 and 10 percentile of monthly accumulative rainfall, which is shown in Figure 6.7. The stimulated daily rainfall data from the Monte Carlo is

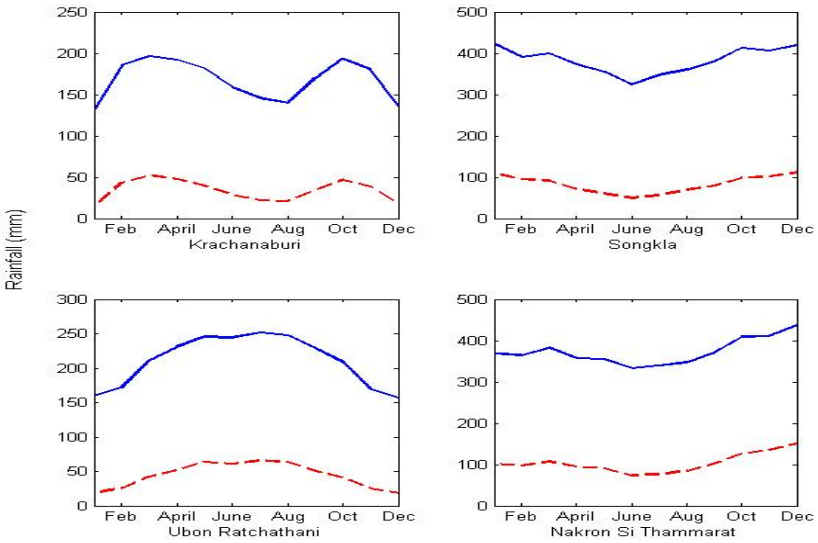
used to generate the monthly cumulative rainfall. There are higher HR strike rainfall levels in Songkla and Nakron Si Thammarat weather stations than weather stations in Kranchanaburi and Ubon Ratchathani. However, the seasonal LR strike rainfall levels of the four weather stations are similar. There is a positive correlation between the HR and LR strike rainfall levels.

Figure 6.8 represents the monthly HR and LR index-insurance premiums with their seasonal strike rainfall levels. The premiums are estimate by using the equation 6.27 and 6.28 with the seasonal strike rainfall level in Figure 6.7 for HR and LR index-insurance premiums for every month. The blue line is the high rainfall (HR) index-insurance premium, and the red dashed line represents the low rainfall (LR) index-insurance premium. The empirical results indicate that the HR rainfall index-insurance premiums of Songkla and Nakron Si Thammarat are more expensive than premiums in Kranchanaburi and Ubon Ratchathani, due to the higher rainfall in southern Thailand. The LR index-insurance premiums are similar. This implies either that there is little chance of drought in all weather stations or a high LR strike rainfall level. Furthermore, the premiums of using the seasonal strike rainfall level are stable. However, Figure 6.9 illustrates considerable fluctuations in premiums when the constant strike rainfall level is used. The HR and LR strike rainfall levels are both 250 mm, and the LR strike rainfall level is 100 mm. A negative correlation in both HR and LR has been found. The findings confirm that if there is a high probability of flooding, farmers do not wish to purchase the drought index-insurance.

The following exercise demonstrates a 30-days index-insurance, as it is provides a more flexible product than the fixed month. The 30-days index-insurance premium with seasonal strike rainfall levels have been shown in Figure 6.10. The HR index-insurance premiums are more volatile than LR and also more costly. The HR rainfall index-insurance premiums in Songkla and Nakron Si Thammarat are more expensive than the other weather stations. The LR rainfall index-insurance premiums do not change much over the year: the average premiums are approximately 300 USD per contract.

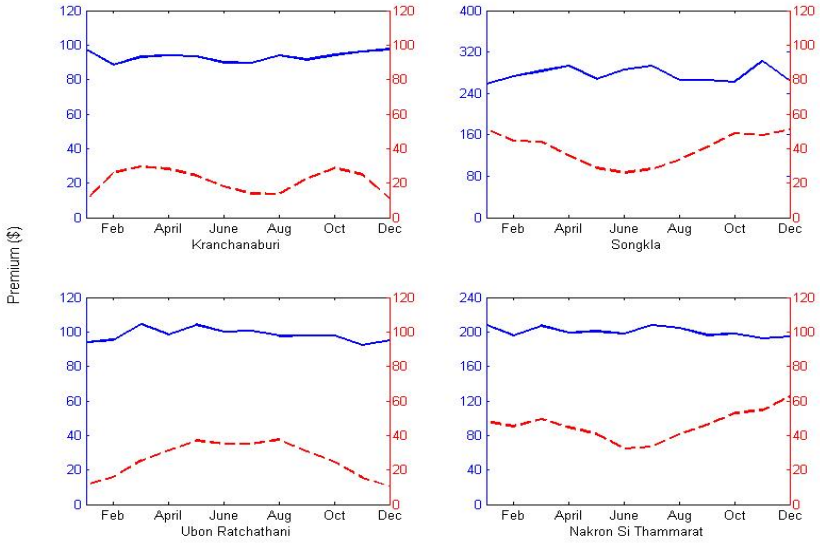
The 30-days index-insurance premium with constant strike rainfall levels are depicted in

Figure 6.7: Monthly seasonal strike rainfall levels



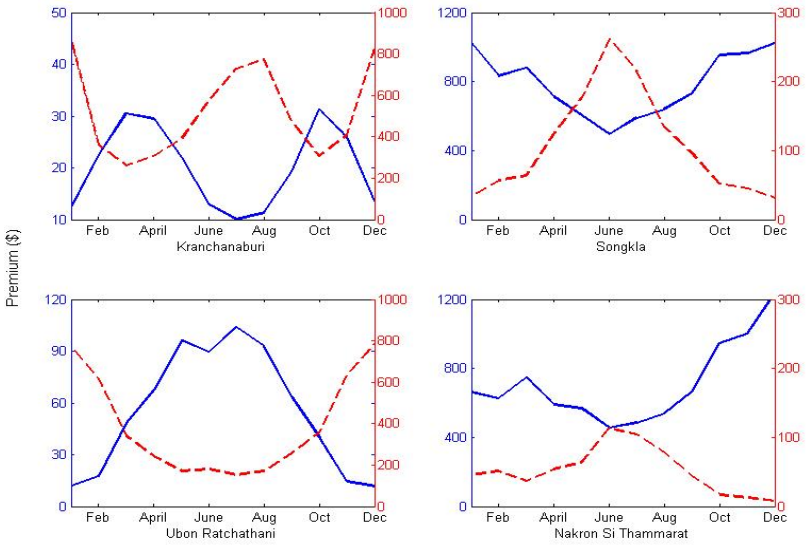

The blue line represents the high rainfall strike level which is 90 percentile of a monthly accumulative rainfall. Moreover, the dashed red line represents the low rainfall strike level that is 10 percentile of a monthly accumulative rainfall.

Figure 6.8: Monthly Rainfall insurance premium with seasonal strike rainfall levels



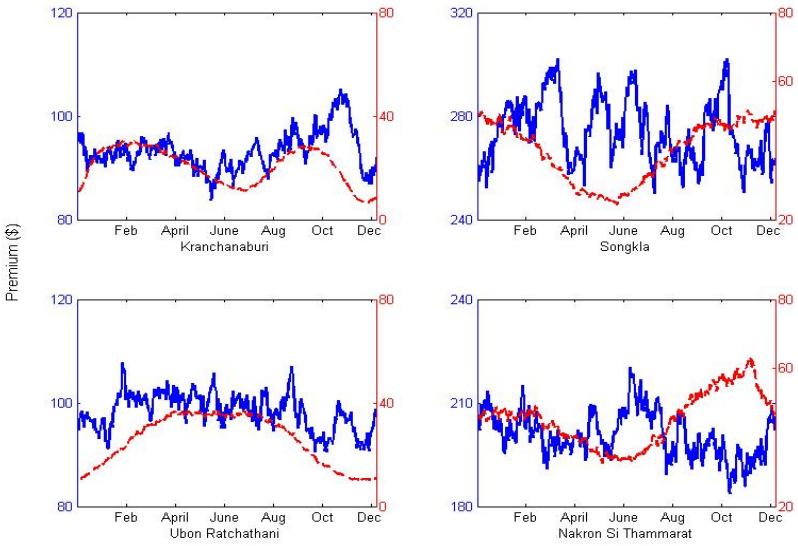

These premiums are calculated from the conditional on the seasonal strike rainfall levels which are 90 and 10 percentile of monthly accumulative rainfall for HR and LR insurance premiums respectively. With every millimetre change in actual rainfall level, the insurer will pay $19.6850 in order to compensate ruin costs. The blue line is the high rainfall (HR) insurance premium. The insurance holder will obtain the claim if the actual rainfall is over the HR strike level. On the other hand, the red dashed line represents the low rainfall (LR) insurance premium. The insured will be compensated when the actual rainfall is lower than the LR strike level.

Figure 6.9: Monthly Rainfall insurance premium with constant strike rainfall levels




These premiums are calculated from the conditional on the constant strike rainfall levels which are 250 mm and 100 mm for HR and LR insurance premiums respectively. With every millimetre change in actual rainfall level, the insurer will pay \$19.6850 in order to compensate ruin costs. The blue line is the high rainfall (HR) insurance premium. The insurance holder will obtain the claim if the actual rainfall is over the HR strike level. On the other hand, the red dashed line represents the low rainfall (LR) insurance premium. The insured will be compensated when the actual rainfall is lower than the LR strike level.

Figure 6.10: 30-days Rainfall insurance premium with seasonal strike rainfall levels

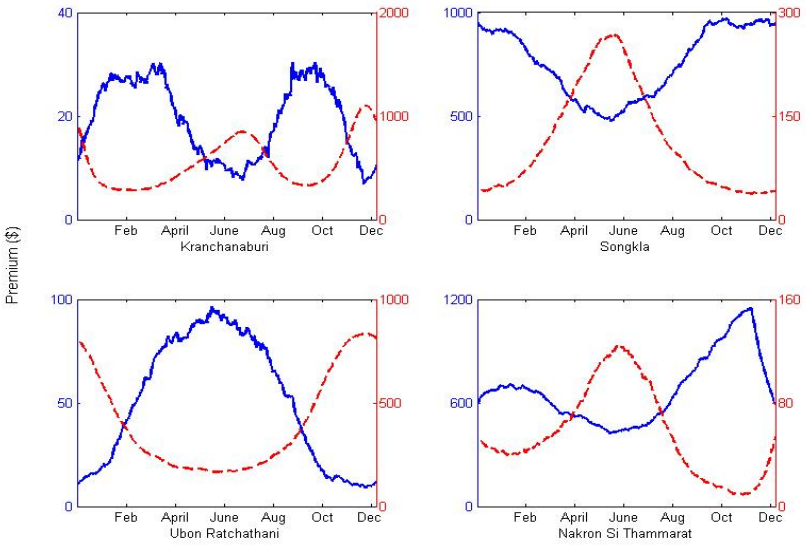



These premiums are calculated from the condition of exercise prices equivalent to an average of 90 per cent rainfall level index. With every millimetre change in actual rainfall level, the insurer will pay $19.6850 in order to compensate ruin costs. The top figure is the high rainfall (HR) insurance premium. The insurance holder will obtain the claim if the actual rainfall is over the HR strike level as shown in Figure 6.7. On the other hand, the lower figure represents the low rainfall (LR) insurance premium. The insured will be compensated when the actual rainfall is lower than the LR strike level.

Figure 6.11. These premiums are more volatile than the seasonal index-insurance premium, and they show a strong negative correlation between HR and LR index-insurance premiums. The LR insurance premiums in Kranchanaburi and Ubon Ratchathani are more expensive than those in Songkla and Nakron Si Thammarat which have higher rainfall level over the year. In contrast, the HR index-insurance premiums in Songkla and Nakron Si Thammarat are higher than those in Kranchanaburi and Ubon Ratchathani. These findings correspond to the fact that heavy rainfall areas must change a higher HR index-insurance premium than dry areas. Hence, this confirms that the constant strike rainfall level causes the seasonal premiums.

The next study is the index-insurance premium estimation with interval constant and seasonal strike rainfall levels. The interval constant strike prices are between 200 and 300 mm for HR, and the strike price ranges between 50 and 150 mm for LR index-insurance premiums. Figures 6.12 and 6.13 show the insurance premiums for monthly and 30-days

Figure 6.11: 30-days Rainfall insurance premium with constant strike rainfall levels



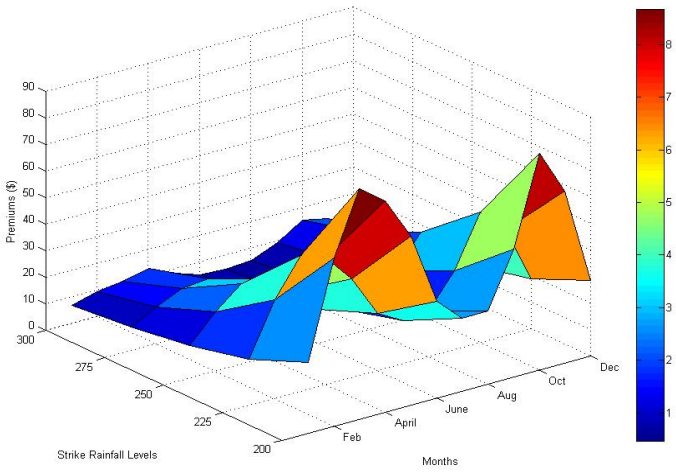

These premiums are calculated from the conditional on the constant strike rainfall level which are 250 mm and 100 mm for HR and LR insurance premiums respectively. With every millimetre change in the actual rainfall level, the insurer will pay \$19.6850 in order to compensate ruin costs. The blue line is the high rainfall (HR) insurance premium. The insurance holder will obtain the claim if the actual rainfall is over the HR strike level. On the other hand, the red dashed line represents the low rainfall (LR) insurance premium. The insured will be compensated when the actual rainfall is lower than the LR strike level.

index-insurance for Kranchanaburi. These results reveal a relatively cheap premium for the high strike price of HR index-insurance; on the other hand, the premiums are expensive when this condition is applied to the LR index-insurance. A negative correlation between HR and LR were discovered, and the seasonal premiums appear when the constant strike rainfall level is imposed. In addition, the seasonal premium is less likely to be affected if the strike rainfall level is high. On the other hand, there is the strong exhibition of seasonality in rainfall premiums of low strike rainfall levels. The premiums of 30-days index-insurance are more volatile than monthly index-insurance. The interval constant index-insurance premium of other weather stations are represented in Figure C.3 to C.8.

The final empirical part is the index-insurance premium with the seasonal strike rainfall levels interval; thus, the target percentile levels are required. The range of HR and LR strike rainfall levels are from 40 to 95 and 5 to 60 percentile of their daily distributions. The monthly and 30-days index-insurance premiums of Kranchanaburi are shown in Figures 6.14 and 6.15. These illustrations show comparable premiums to previous findings. There are, for example, negative correlations between HR and LR premiums and expensive premiums when the agreed strike rainfall levels are low for HR index-insurance. The seasonal strike levels cause consistent premiums over the year. Figures C.9 to C.14 illustrate the graphic premium for other weather stations. It should be noted that the HR index-insurance premium is more expensive for Songkla and Nakron Si Thammarat than for the other weather stations. This indicates the effect of the location on index-insurance premiums.

Figure 6.12: Monthly insurance premium of constant strike rainfall levels interval of Kranchanaburi

- HR Index-Insurance Premium




- LR Index-Insurance Premium

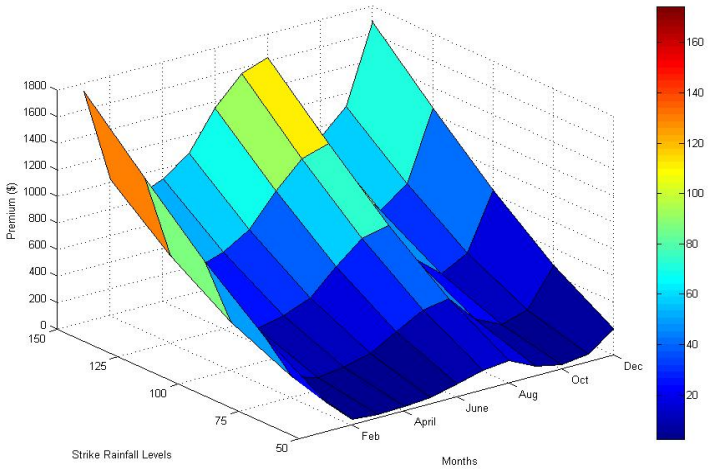
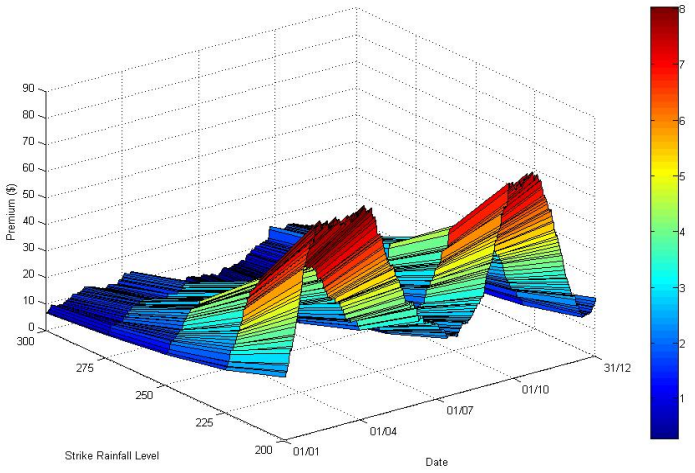


Figure 6.13: 30-days insurance premium of constant strike rainfall levels interval of Kranchanaburi

- HR Index-Insurance Premium




- LR Index-Insurance Premium

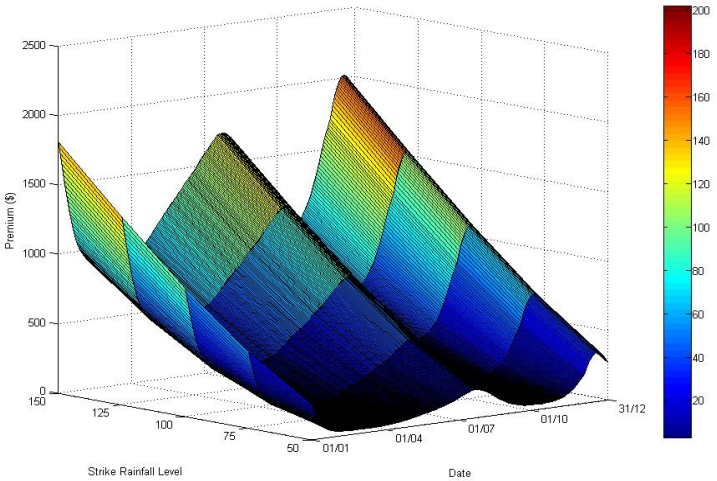
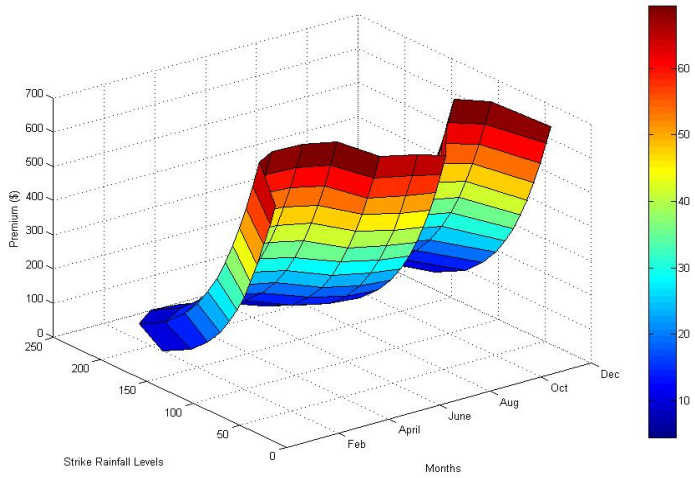


Figure 6.14: Monthly insurance premium of seasonal strike rainfall levels interval of Kranchanaburi

- HR Index-Insurance Premium




- LR Index-Insurance Premium

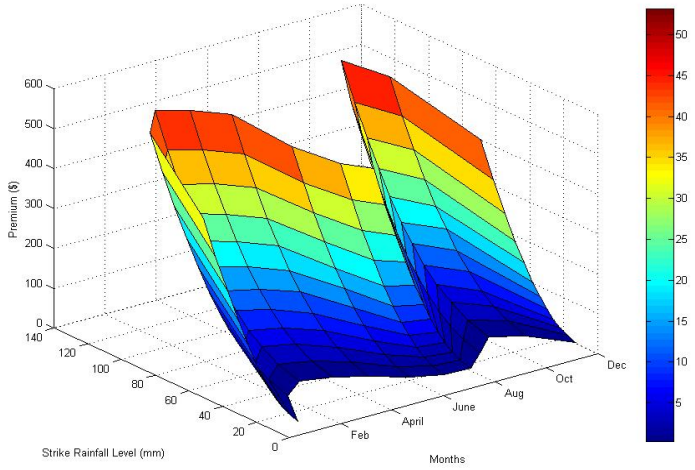
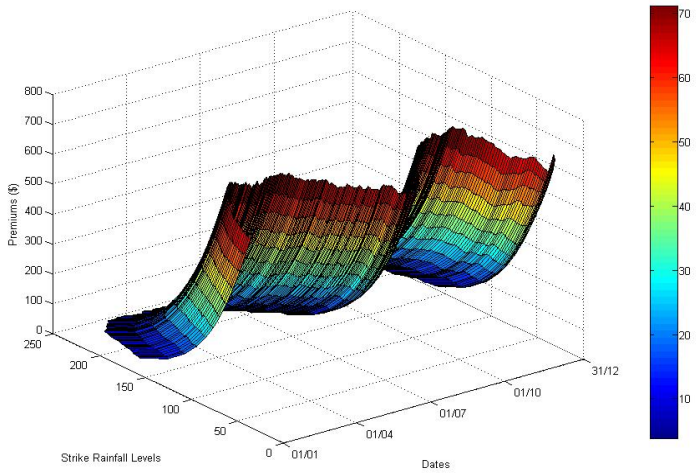
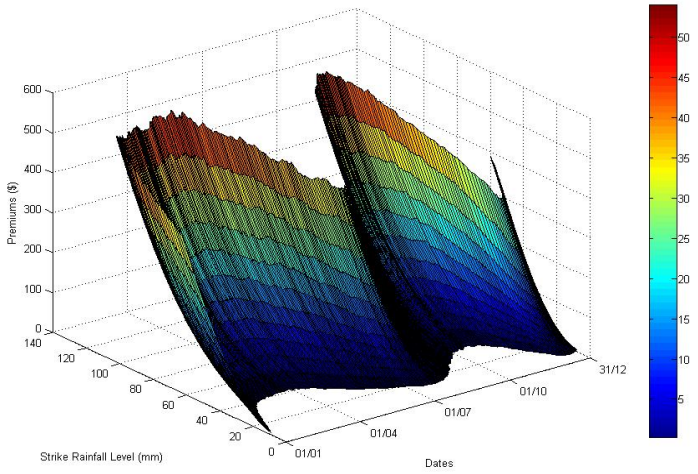


Figure 6.15: 30-days insurance premium of seasonal strike rainfall levels interval of Kranchanaburi

- HR Index-Insurance Premium




- LR Index-Insurance Premium



## 6.6 Conclusion

The main contribution of this chapter is to propose a rainfall model for four weather stations in a monsoon country, Thailand. In general, many agribusinesses encounter unpredictable losses from changes in climate, especially from droughts and floods. Therefore, hedging against unpredictable events could benefit farmers. The weather stations examined in this chapter were Ubon Ratchathani, Kranchanburi, Nakron Si Thammarat and Songkla. These four weather stations are the largest areas for harvesting rice, white sugar and rubber, with Nakron Si Thammarat and Songkla both being areas for rubber. These three agricultural products generate a considerable income for Thai farmers and are the main exports of Thailand. All daily rainfall data was collected from the Thai Meteorological Department and covered the period of January 1998 to December 2011.

This chapter is initially concerned with data analysis: the non-negative and very high excess kurtosis numbers are found. The average rainfall of the four weather stations correspond with the water demands of each agriculture product, for example, as rubber needs a high amount of water to grow, so the average rainfall level is relatively high in both Nakron Si Thammarat and Songkla. The seasonal pattern is significant, and it appears in the analysis.

A two-step approach is considered for rainfall modelling. This concept is common in statistics and finance, and expectation and binomial options pricing models use a dual approach. Our two-step approach was as follows: first, the conditional probability with seasonality components using a trigonometric function was composed with an ordinary least square (OLS) approach. Second, the rainfall estimation by the rainfall hybrid distribution was determined. This probability distribution consists of a seasonally adjusted Weibull distribution, which captures moderate rainfall, and an Extreme Value distribution, which captures extreme to heavy rainfall.

Monte Carlo methods are used to simulate the daily data in order to compare our model's performance with the actual data. The predictive rainfall represents the ability of forecasting, for instance, whether or not the mean and the maximum estimated and actual rainfall are

similar if it is accuracy.

Moreover, the application of rainfall modelling in insurance pricing is demonstrated. The insurance contract for 30-days and monthly period frameworks are set. Moreover, there are two main kinds of strike price: high rainfall (HR) and low rainfall (LR). This chapter attempts to create a more realistic strike price by assuming the constant and seasonal strike prices for both types of rainfall insurances. The results indicate that the constant strike price formulates a seasonal insurance premium and vice versa. In addition, we find that the premium fluctuates over the year and is also dependent on the location. For the future research, the rainfall estimation in one single stage could provide more efficient to calibrate the model or the variable of distance between the weather station and the farm should be considered.

# Chapter 7

# Conclusions and Further Research

## 7.1 Conclusions

In this study of risk management tools and develop financial modelling for an agricultural exporter. We have found that the most important risks for farmers and agribusinesses are price risk and production risk, which both potentially cause unexpected losses. The problem of price and production risk led to three main research contributions which mainly focus on forecast modelling. These are price risk modelling, convenience yield modelling and rainfall modelling. At the beginning of this thesis, we reviewed the related literature and provided the background of Thai agricultural markets. We determined that the seasonal pattern is an essential phenomenon which should be incorporated in agriculture forecasting models. The trigonometric function is used to represent the seasonal effect in both price risk modelling and rainfall modelling. The advantage of using the trigonometric function is that a forecaster is able to capture the high frequency seasonal pattern without using many dummy variables.

The first contribution was the agricultural price risk modelling, which became attractive due to very high volatility during 2007-2008. This volatility caused high potential losses for farmers or exporters. Three main Thai agricultural exports are used in this study, however all prices are collected from the active agriculture futures exchange markets, for instance rubber from TOCOM, rough rice from CBOT and white sugar from LIFFE, London.

A GJR-GARCH (1,1) with seasonality components was composed. Weekly seasonal components illustrate the trading behaviour in the futures markets, and yearly seasonal variables represent harvesting and growing patterns. Furthermore, the fat-tailed error distributions,

which are Standardised-t and GED error distributions, are used to capture the high kurtosis in our samples and compare the estimating performances with Gaussian error distribution. The empirical results strongly indicate that including the seasonality component outperforms confirming by likelihood ratio test; however, the asymmetric affect appears differently across products. Only a negative asymmetric variable is appropriate to incorporate into the agricultural volatility models.

The second part of seasonal volatility study examines the implications of the proposed model in Value-at- Risk (VaR). The volatility process is estimated on a daily basis. The comparison of one day and 5 days horizon VaR are performed. Failure and DQ tests are employed to justify their performances. The results illustrate that the VaR estimations with fat-tailed error distribution are better fitted than those of a Gaussian model for both one day and 5 days horizons. In addition, the GED error distribution outperforms.

The second contribution is the net convenience yield modelling. We started this study with a determination of the net convenience yield behaviours of seven agriculture futures prices. Seven agriculture futures contract prices from leading international futures exchange markets are used in this empirical study. This data consists of rubber (from Tokyo Commodity Exchange Market), white sugar (from LIFFE, London), raw sugar, cotton, coffee (from New York Board of Trade), rough rice and corn (from Chicago Board of Trade). The net convenience yield is directly calculated from the different times to maturity of futures contracts by assuming the shortest time to maturity as a spot price. The first stylized fact that this study found was that the short term pricing approach is more affected by the net convenience yield than the long term pricing process.

The second objective of the convenience yield study is to model the net convenience yield. It is based on the heteroskedasticity test. The modification of the heteroskedasticity test employed by Liu and Tang (2011) can be rearranged to an autoregressive model (AR(1) model). Heteroskedaticity has been found in all samples; moreover, the new heteroskedasticity test has been introduced, and it produced consistent results. Due to the very high kurtosis of all the samples, estimated comparisons between Standardised-t and Gaussian error distribution are

presented. Moreover, two time varying volatility models, a generalized autoregressive conditional heteroskedasticity (GARCH) and an integrated generalized autoregressive conditional heteroskedasticity (IGARCH), are used. The final estimations indicate that in convenience yield modelling with GARCH (1,1), Standardised-t performs better than IGARCH (1,1) with Gaussian or Standardised-t and GARCH (1,1)-Gaussian.

The final contribution of the convenience yield study is the determination of the exchange rate effect on the benefit of holding a physical agricultural product. As we know that currency depreciation is an advantage for exporters, the empirical results indicate that the depreciation in the exchange rate of leading export countries eliminates the benefit of holding the physical agricultural product. In addition, the net convenience yield reduction produces a low futures price. These consequences can also be explained by the law of supply and demand. Hence, the leading exporters do not have any advantage from holding these agricultural commodities and desire to export their commodities.

The final chapter is rainfall modelling. An analysis of the rainfall characteristics of four weather stations in Thailand, which are the main growing areas for rubber, rice and sugar cane, was conducted. Seasonality dominates in rainfall level and unexpected high rainfall events are detected from the analysis. Hence, we proposed a hybrid distribution model which captures the distinctive moderate and extreme heavy rainfall features.

The rainfall model is based on a two-step approach. Initially, an estimation of seasonal conditional probability was performed. Then, an intensity rainfall estimation from the hybrid distribution, the second approach, was performed. This probability error distribution consists of a seasonal-Weibull distribution that represents moderate rainfall, and an Extreme Value distribution that captures extremely heavy rainfall. The comparison of a seasonal-mean model and a non seasonal- mean model demonstrates the importance of the inclusion of seasonality in providing a more realistic a representation of daily rainfall.

Our proposed model introduces the benefit of seasonality inclusion for insurance. High rainfall (HR) and low rainfall (LR) insurances are created for hedging against potential losses from unexpected weather events. The empirical application demonstrates the rainfall insurance

premium calculation. Monte Carlo methods are used to simulate the daily data in order to compare our model performance with the actual data and to study the rainfall insurance premium. Monthly and 30-days HR and LR insurance premiums are illustrated with constant and seasonal strike prices. We found that the premium fluctuates over the year and is also dependent on location.

## 7.2 Further Research

In future research, we possibly consider either extending our significant contributions in different applications or continuing to add to the understanding of time series analysis and non-normal probability distributions to develop new research in commodities. As the seasonal volatility model is the main outcome of the price risk management chapter, applications in the pricing process or trading strategy would be considered. This could provide more accuracy in option pricing and portfolio choice. At the present, the commodity is an attractive asset class because it can be effectively used to hedge the inflation risk. However, there are many assets that depend on the season, such as livestock and electricity. Hence, it would be useful to implement the proposed seasonal volatility model on these samples. In regards to the second contribution, continued research through focusing on the time to decay of agricultural commodities such as dairy products or grain could be considered, as the benefit of holding the physical commodity could decrease exponentially. This decrease could affect convenience yield and futures prices. Moreover, as our findings indicate that the net convenience yield approaches to zero in long term contracts because of the production cycle, the optimal holding period should be investigated. The last contribution is similar to commercial insurance. We have learnt how to create an effective hybrid distribution. We found that weather insurance can be improved by involving the distance between the field and the weather station. This distance concept has been used previously in many pricing approaches, especially in real estate, for instance, a more expensive house is usually located close to a business centre. Therefore, the distance factor should be incorporated in the rainfall modelling to avoid location risk.

# References


Akram, Q.F. (2009). Commodity Prices, Interest Rates and the Dollar. *Energy Economics*, 31, pp. 838–851.

Alaton, P., Djehiche, B. & Stillberger, D. (2002). On Modelling and Pricing Weather Derivatives. *Applied Mathematical Finance*, 9(1), pp. 1–20.

Baek, J. & Koo, W. (2007). Dynamic Interrelationships between the US Agricultural Trade Balance and the Macroeconomy. *Journal of Agricultural and Applied Economics*, 39(3), pp. 457–470.

Baek, J. & Koo, W.W. (2010). The U . S . Agricultural Sector and the Macroeconomy. *Agricultural and Appllied Economics*, 3(August), pp. 457–465.

Bahmani-Oskooee, M. (1985). Devaluation and the J-curve: Some Evidence from LDCs. *The review of Economics and Statistics*, 67(3), pp. 500–504.

Bahmani-Oskooee, M., Ardalani, Z. & Bolhasani, M. (2010). Exchange Rate Volatility and US Commodity Trade with the Rest of the World. *International Review of Applied Economics*, 24(5), pp. 511–532.

Bank of Thailand (2012). Statistics, Available from http://www.bot.or.th/English/Statistics/Pages/index1.aspx [Accessed 15 March 2012].

Beck, S. (2001). Autoregressive Conditional Heteroscedasticity in Commodity Spot Prices. *Journal of Applied Econometrics*, 16(2), pp. 115–132.

Bekaert, G. & Wu, G. (2000). Asymmetric Volatility and Risk in Equity Markets. *The Review of Financial Studies*, 13(1), pp. 1–42.

Berument, H. & Kiymaz, H. (2001). The Day of the Week Effect on Stock Market Volatility. *Journal of Economics and Finance*, 25(2), pp. 181–193.

Biagini, F. & Björk, T. (2007). On the Timing Option in a Futures Contract. *Mathematical Finance*, 17(2), pp. 267–283.

Bjerksund, P. (1991). Contingent Claims Evaluation when the Convenience Yield is Stochastic : Analytical Results, Working Paper, Norwegian School of Economics and Business Administration.

Black, F. (1976). The Pricing of Commodity Contracts. *Journal of financial economics*, 3, pp. 167–179.

Black, F. & Scholes, M. (1973). The Pricing of Options and Corporate Liabilities. *The Journal of Political Economy*, 81(3), pp. 637–654.

Bollerslev, T. (1986). Generalized Autoregressive Conditional Heteroskedasticity. *Journal of Econometrics*, 31, pp. 307–327.

Bollerslev, T. (2008). Glossary to ARCH ( GARCH ), Working Paper 2008-49, University of Copenhagen.

Borovkova, S. & Geman, H. (2007). Seasonal and Stochastic Effects in Commodity Forward Curves. *Review of Derivatives Research*, 9(2), pp. 167–186.

Breusch, T. & Pagan, A. (1979). A Simple Test for Heteroscedasticity and Random Coefficient Variation. *Econometrica*, 47(5), pp. 1287–1294.

Brockett, P., Wang, M. & Yang, C. (2005). Weather Derivatives and Weather Risk Management. *Risk Management and Insurance Review*, 8(1), pp. 127–140.

Broussard, J. & Booth, G. (1998). The Behavior of Extreme Values in Germany's Stock Index Futures: An Application to Intradaily Margin Setting. *European Journal of Operational Research*, 104, pp. 393–402.

Cao, M., Li, A. & Wei, J. (2004). Precipitation Modeling A Frontier in Weather Derivatives. *The Journal of Alternative Investment*, Fall, pp. 93–100.

Cartea, A. & Figueroa, M. (2005). Pricing in Electricity Markets: A Mean Reverting Jump Diffusion Model with Seasonality. *Applied Mathematical Finance*, 12(4), pp. 313–335.

Catherine, C.S.S., Evans, M., Hastings, N. & Peacock, B. (2011). *Statistical distributions*. Chichester: John Wiley & Sons, Inc., 4th edition.

Chantarat, S., Barrett, C.B., Mude, A.G. & Turvey, C. (2007). Using Weather Index Insurance to Improve Drought Response for Famine Prevention. *American Journal of Agricultural Economics*, 89(5), pp. 1262–1268.

Chen, T.f., Chung, H. & Ji-Chai, L. (2008). The Information Content of the Implied Convenience Yield: Using American Call Option Based Structural Model, Working Paper, National Chiao Tung University.

Chen, Y.c. & Rogoff, K. (2003). Commodity Currencies. *Journal of International Economics*, 60(1), pp. 133–160.

Christoffersen, P.F. (2003). *Elements of Financial Risk Management*. London: Elsevier.

Climatological Center: Thailand Meteorological Department (2012). Rainfall and Severe Flooding Over Thailand in 2011, Available from http://www.tmd.go.th/en/[Accessed 15 March 2012].

Dickson, D. (2005). *Insurance Risk and Ruin*. January, Cambridge: Cambridge University Press, 1st edition.

Dincerler, C., Khoker, Z. & Simin, T. (2005). An Empirical Analysis of Commodity Convenience Yields, Working Paper, University of Western Ontario.

Doran, J. & Ronn, E. (2008). Computing the Market Price of Volatility Risk in the Energy Commodity Markets. *Journal of Banking and Finance*, 32(12), pp. 2541–2552.

Du, W. & Wang, H. (2004). Price behavior in China's wheat futures market. *China Economic Review*, 15(2), pp. 215–229.

Engle, R. (1982). Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation. *Econometrica*, 50(4), pp. 987–1007.

Engle, R. (2001). GARCH 101: The Use of ARCH/GARCH Models in Applied Econometrics. *Journal of Economic Perspectives*, 15(4), pp. 157–168.

Engle, R. & Manganelli, S. (2004). CAViaR: Conditional Autoregressive Value at Risk Regression Quantile. *Journal of Business and Economic Statistics*, 22(4), pp. 367–381.

Engle, R. & Ng, V.K. (1993). Time-Varying Volatility and the Dynamic Behavior of the Term Structure. *Juornal of Money, Credit and Banking*, 25(3), pp. 336–349.

Engle, R. & Patton, A. (2001). What Good is a Volatility Model?, Working paper no. S-DRP-01-03, New York University.

Evans, M., Hastings, N. & Peacock, B. (2000). *Statistical distributions*. New York: John Wiley & Sons, Inc.

Fabozzi, F.J., Füss, R. & Kaiser, D.G. (2008). *The Handbook of Commodity Investing*. Hoboken, NJ, USA: John Wiley & Sons, Inc.

Fackler, P. (1986). Futures Price Volatility: Modeling Non-Constant Variance. In: *AAAE Annual Meetings, Reno, Nevada, July 27-30*, volume 68.

Fama, E.F. & French, K.R. (1987). Commodity Futures Prices: Some Evidence on Forecast Power, Premiums, and the Theory of Storage. *The Journal of Business*, 60(1), pp. 55–73.

Federico, G. (2005). *Feeding The World: An Economic History of Agriculture, 1800-2000*, volume 9780691138. Oxford: Princeton University Press.

Felkner, J., Tazhibayeva, K. & Townsend, R. (2009). Impact of Climate Change on Rice Production in Thailand. *The American Economic Review*, 99(2), pp. 205–210.

Fischer, S. (1978). Call Option Pricing When the Exercise Price is Uncertain, and the Valuation of Index Bonds. *The Journal of Finance*, 33(1), pp. 169–176.

Food and Agriculture Organization of the United Nations (2011). Statistics Available from http://www.fao.org/corp/statistics/en/ [Accessed 8 August 2011].

Galvani, V. & Plourde, A. (2010). Portfolio Diversification in Energy Markets. *Energy Economics*, 32(2), pp. 257–268.

Geman, H. (2005). *Commodities and Commodity Derivatives: Modelling and Pricing for Agriculturals, Metals, and Energy*. Chichester: John Wiley & Sons, Inc., 1st edition.

Geman, H. (2009). *Risk Management in Commodity Markets: From Shipping to Agricuturals and Energy*. March, Chichester: John Wiley & Sons, Inc., 1st edition.

Gibson, R. & Schwartz, S. (1990). Stochastic Convenience Yield and the Pricing of Oil Contingent Claims. *Journal of Finance*, 45(3), pp. 959–976.

Glejser, H. (1969). A New Test for Heteroskedasticity. *Journal of the American Statistical Association*, 64(325), pp. 316–323.

Glosten, L., Jagannathan, R. & Runkle, D. (1993). On the Relation between the Expected Value and the Volatility of the Nominal Excess Return on Stocks. *Journal of finance*, 48(5), pp. 1779–1801.

Goldberg, P. & Knetter, M. (1997). Goods Prices and Exchange Rates: What Have We Learned? *Journal of Economic Literature*, 35(3), pp. 1243–1272.

Hamilton, J. (1994). *Time series analysis*. Chichester: Princeton University Press.

Hannan, E., Terrell, R. & Tuckwell, N. (1970). The Seasonal Adjustment of Economic Time Series. *International Economic Review*, 11(1), pp. 24–52.

Hanson, J., Dismukes, R., Chambers, W., Greene, C. & Kremen, A. (2004). Risk and Risk Management in Organic Agriculture: Views of Organic Farmers. *Renewable Agriculture and Food Systems*, 19(04), pp. 218–227.

Harvey, A. (1976). Estimating Regression Models with Multiplicative Heteroscedasticity. *Econometrica*, 44(3), pp. 461–465.

Hatzinikolaou, D. & Polasek, M. (2005). The Commodity-Currency View of the Australian Dollar: A Multivariate Cointegration Approach. *Journal of Applied Economics*, 13(1), pp. 81–99.

Hayakawa, K. & Kimura, F. (2009). The Effect of Exchange Rate Volatility on International Trade in East Asia. *Journal of the Japanese and International Economies*, 23(4), pp. 395–406.

Hazell, P. & Hess, U. (2010). Drought Insurance for Agricultural Development and Food Security in Dryland Areas. *Food Security*, 2(4), pp. 395–405.

Heaney, R. (2002). Approximation for Convenience Yield in Commodity Futures Pricing. *Journal of Futures Markets*, 22(10), pp. 1005–1017.

Heath, D., Jarrow, R. & Morton, A. (1992). Bond Pricing and the Term Structure of Interest Rates: A New Methodology for Contingent Claims Valuation. *Econometrica*, 60(1), pp. 77–105.

Heinkel, R., Howe, M.E. & Hughes, J.S. (1990). Commodity Convenience Yields as an Option Profit. *Journal of Futures Markets*, 10(5), pp. 519–533.

Hess, U., Richter, K. & Stoppa, A. (2004). Weathere Risk Management for Agriculture and Agri-Business in Developing Countries. In: *Climate Risk and the Weather Market, Financial Risk Management with Weather Hedges.*, London: International Finance Corporation, The World Bank, 1st edition, pp. 1–16.

Huang, B., Chen, M., Chang, C. & Mcaleer, M. (2009). Modelling Risk in Agricultural Finance: Application to the Poultry Industry in Taiwan. *Mathematics and Computers in Simulation*, 79(5), pp. 1472–1487.

Hudson, D. & Coble, K. (1999). Harvest Contract Price Volatility for Cotton. *Journal of Futures Markets*, 19(6), pp. 717–733.

Hull, J. (2008). *Options, Futures and other Derivatives*. Upper Saddle River, NJ: Prentice Hall, 7th edition.

Johnson, N.L., Kotz, S. & Balakrishnan, N. (1994). *Continuous Univariate Distributions*. New York: Wiley, 2nd edition.

Johnston, J. & DiNardo, J. (2007). *Econometric Methods*. London: Mcgraw-Hill Publishing Co, 4th edition.

Jorion, P. (2007). *Value at Risk: The New Benchmark for Managing Financial Risk*, volume 0071464956. New York: McGraw-Hill, 3rd edition.

Just, D.R., Wolf, S. & Zilberman, D. (2003). Principles of Risk Management Service Relations in Agriculture. *Agricultural Systems*, 75(2), pp. 199–213.

Kaldor, N. (1939). Speculation and Economic Stability. *The Review of Economic Studies*, 7(1), pp. 1–27.

Karali, B. & Thurman, W.N. (2010). Components of Grain Futures Price Volatility. *Journal of Agricultural and Resource Economics*, 35(2), pp. 167–182.

Kenyon, D., Kling, K., Jordan, J., Seale, W. & McCabe, N. (1987). Factors Affecting Agricultural Futures Price Variance. *Journal of Futures Markets*, 7(1), pp. 73–91.

Kiymaz, H. & Berument, H. (2003). The Day of the Week Effect on Stock Market Volatility and Volume: International Evidence. *Review of Financial Economics*, 12(4), pp. 363–380.

Kleiber, C. & Kotz, S. (2003). *Statistical Size Distributions in Economics and Actuarial Sciences*. Hoboken, N.J.: Wiley-Interscience.

Knetsch, T. (2007). Forecasting the Price of Crude Oil via Convenience Yield Predictions. *Journal of Forecasting*, 26, pp. 527–549.

Kocagil, A. (2004). Optionality and Daily Dynamics of Convenience Yield Behavior: an Empirical Analysis. *Journal of Financial Research*, 27(1), pp. 143–158.

Koekebakker, S. & Lien, G. (2004). Volatility and Price Jumps in Agricultural Futures Prices-Evidence from Wheat Options. *American Journal of Agricultural Economics*, 86(4), pp. 1018–1031.

Kohers, G., Kohers, N., Pandey, V. & Kohers, T. (2004). The Disappearing Day-of-the-Week Effect in the World's Largest Equity Markets. *Applied Economics Letters*, 11(3), pp. 167–171.

Kotz, S. & Nadarajah, S. (2000). *Extreme Value Distributions: Theory and Applications*. London: Imperial College Press, 1st edition.

Kotz, S., Balakrishnan, N. & Johnson, N.L. (1972). *Continuous Multivariate Distributions. Volume 1 Models and Applications*, volume 1. New York: Wiley, 2nd edition.

Lamoureux, C. & Lastrapes, W. (1990). Persistence in Variance, Structural Change, and the GARCH Model. *Journal of Business & Economic Statistics*, 8(2), pp. 225–234.

Lin, W.T. & Duan, C.W. (2006). Oil Convenience Yields Estimated Under Demand/Supply Shock. *Review of Quantitative Finance and Accounting*, 28(2), pp. 203–225.

Liu, K.E., Geaun, J. & Lei, L.F. (2001). Optimal Hedging Decisions for Taiwanese Corn Traders on the Way to Liberalisation. *Agricultural Economics*, 25, pp. 303–309.

Liu, P. & Tang, K. (2011). The Stochastic Behavior of Commodity Prices with Heteroskedasticity in the Convenience Yield. *Journal of Empirical Finance*, 18, pp. 211–224.

Liu, W. & Morley, B. (2009). Volatility Forecasting in the Hang Seng Index using the GARCH Approach. *Asia-Pacific Financial Markets*, 16(1), pp. 51–63.

Liu, X., Cheng, S., Wang, S., Hong, Y. & Li, Y. (2008). An Empirical Study on Information Spillover Effects Between the Chinese Copper Futures Market and Spot Market. *Physica A: Statistical Mechanics and its Applications*, 387(4), pp. 899–914.

Longstaff, F. (1995). How Much Can Marketability Affect Security Values? *Journal of finance*, 50(5), pp. 1767–1774.

Lucia, J. & Schwartz, E. (2002). Electricity Prices and Power Derivatives: Evidence From the Nordic Power Exchange. *Review of Derivatives Research*, 5(1), pp. 5–50.

Malcolm, H.D. (2011). *Extreme Events : Robust Portfolio Construction in the Presence of Fat Tails*. Chichester: John Wiley & Sons, Inc., 1st edition.

Malick, W. & Ward, R. (1987). Stock Effects and Seasonality in the fcoj Futures Basis. *Journal of Futures Markets*, 7, pp. 157–167.

Manfredo, M. & Richards, T. (2009). Hedging with Weather Derivatives: A Role for Options in Reducing Basis Risk. *Applied Financial Economics*, 19(2), pp. 87–97.

Martens, M., van Dijk, D. & de Pooter, M. (2009). Forecasting S&P 500 Volatility: Long Memory, Level Shifts, Leverage Effects, Day-of-the-Week Seasonality, and Macroeconomic Mnnouncements. *International Journal of Forecasting*, 25(2), pp. 282–303.

Meuwissen, M., Huirne, R. & Hardaker, J. (2001). Risk and Risk Management: An Empirical Analysis of Dutch Livestock Farmers. *Livestock Production Science*, 69, pp. 43–53.

Milonas, N.T. & Thomadakis, S.B. (1997). Convenience Yields as Call Options: An Empirical Analysis. *Journal of Futures Markets*, 17(1), pp. 1–15.

Miltersen, K. & Schwartz, E. (1998). Pricing of Options on Commodity Futures with Stochastic Term Structures of Convenience Yields and Interest Rates. *The Journal of Financial and Quantitative Analysis*, 33(1), pp. 33–59.

Mohan, S. (2007). Market-Based Price-Risk Management for Coffee Producers. *Development Policy Review*, 25(3), pp. 333–354.

Musshoff, O., Odening, M. & Xu, W. (2011). Management of Climate Risks in Agriculture-will Weather Derivatives Permeate? *Applied Economics*, 43(9), pp. 1067–1077.

Myers, R. & Hanson, S. (1993). Pricing Commodity Options when the Underlying Futures Price Exhibits Time-Varing Volatility. *American Journal Agricultural Economics*, Feb(73), pp. 121–130.

NatCatSERVICE (2012). Annual Statistic 2011Available from http://www.munichre.com/en/reinsurance/business/non- life/georisks/natcatservice/annual_statistics.aspx [Accessed 10 May 2012].

National Statistical Office Thailand (2012). People & Society Statistics Available from http://web.nso.go.th/en/stat_theme_socpop.htm [Accessed 15 March 2012].

Nelson, D. (1991). Conditional Heteroskedasticity in Asset Returns: A New Approach. *Econometrica*, 59(2), pp. 347–370.

Nieto, J.D., Cook, S.E., Läderach, P., Fisher, M.J. & Jones, P.G. (2010). Rainfall Index Insurance to help Smallholder Farmers Manage Drought Risk. *Climate and Development*, 2, pp. 233–247.

Odening, M., Musshoff, O. & Xu, W. (2007). Analysis of Rainfall Derivatives Using Daily Precipitation Models: Opportunities and Pitfalls. *Agricultural Finance Review*, Spring, pp. 135–156.

Office of Agricultural Economics (2012). Agricultural Statistics Available from http://www.oae.go.th/oae_report/stat_agri/main.php?lang=en [Accessed 20 March 2012].

Office of The Cane and Sugar Board (2012). Sugar Cane Statistics Available from http://www.ocsb.go.th/th/cms/index.php?SystemModuleKey=cuntry [Accessed 20 March 2012].

Office of the Permanent Secretary Ministry of Commerce (2012). Thailand Trading Report Available from http://www2.ops3.moc.go.th/# [Accessed 15 March 2012].

Oglend, A. & Sikveland, M. (2008). The Behaviour of Salmon Price Volatility. *Marine Resource Economics*, 23(4), pp. 487–506.

Osborn, D.R. & Ghysels, E. (2001). *The Econometric Analysis of Seasonal Time Series*. UK: Cambridge University Press.

Pindyck, R. (2004). Volatility and Commodity Dynamic. *The Journal of Future Markets*, 24, pp. 1029–1047.

Poon, S.H. & Granger, C. (2005). Practical Issues in Forecasting Volatility. *Financial Analysts Journal*, 61(1), pp. 45–56.

Power, G.J. & Vedenov, D. (2010). Dealing with Downsind Risk in a Multi Commodity Setting A Case for A Texas Hedge ? *The Journal of Futures Markets Futures*, 30(3), pp. 290–304.

Power, G. & Turvey, C. (2008). On Term Structure Models of Commodity Futures Prices and the Kaldor-Working Hypothesis. In: *The NCCC-134 Conference on Applied Commodity Price Analysis, Forecasting, and Market Risk Management. St. Louis, MO.*, NCCC-134 Conference on Applied Commodity Price Analysis, Forecasting, and Market Risk Management.

Ranjan, N. (2005). Role of Commodity Exchanges, Futures & Options (A Case Study on Soya Oil), Working Paper, National Bank for Agriculture and Rural Development Mumbai.

Reiss, R. & Thomas, M. (2007). *Statistical Analysis of Extreme Values : with Applications to Insurance , Finance , Hydrology and other Fields*. Basel: Birkhäuser, 3rd edition.

Richter, M.C. & Sorensen, C. (2000). Stochastic Volatility and Seasonality in Commodity Futures and Options : The Case of Soybeans, Working paper, Department of Finance, Copenhagen Business School.

Roberts, M. (2001). Commodities, Options, and Volatility: Modelling Agricultural Futures Prices, Working Paper, The Ohio State University.

Routledge, B.R., Seppi, D.J. & Spatt, C.S. (2000). Equilibrium Forward Curves for Commodities. *The Journal of Finance*, 55(3), pp. 1297–1338.

Rubber Research Institute of Thailand (2010). Information for the Rubber Growth's Location, Available from http://www.rubberthai.com/statistic/stat_index.htm [Accessed 10th March 2010].

Rubber Research Institute of Thailand (2012). Rubber Exporting Volume by Destinations, Available from http://www.rubberthai.com/statistic/stat_index.htm [Accessed 20 March 2012].

Samuelson, P. (1965). Proof that Properly Anticipated Prices Fluctuate Randomly. *Management Review*, 6(2), pp. 41–49.

Sanso, B. & Guenni, L. (1999). A Stochastic Model for Tropical Rainfall at a Single Location. *Journal of Hydrology*, 214, pp. 64–73.

Schaffnit-Chatterjee, C. (2010). Risk Management in Agriculture: Towards Market Solutions in the EU. *Deutsche Bank Research*, Oct, pp. 1–31.

Schwartz, E. (1997). The stochastic behavior of commodity prices: Implications for valuation and hedging. *The Journal of Finance*, 52(3), pp. 923–973.

Seguro, J. & Lambert, T. (2000). Modern Estimation of the Parameters of the Weibull Wind Speed Distribution for Wind Energy Analysis. *Journal of Wind Engineering and Industrial Aerodynamics*, 85, pp. 75–84.

Singh, J. (2007). Futures Markets and Price Stabilization-Evidence from Indian Hessian Market. *Finance India : The Quarterly Journal of Indian Institute of Finance.*, 21(1), pp. 151–166.

Skees, J., Gober, S., Varangis, P., Lester, R.R. & Kalavakonda, V. (2001). Developing Rainfall-based Index Insurance in Morocco, Working Paper, The World Bank, Policy Research 2577.

Sorensen, C. (2002). Modeling Seasonality in Agricultural Commodity Futures. *Journal of Futures Markets*, 22(5), pp. 393–426.

Stifel, D. & Randrianarisoa, J. (2006). Agricultural Policy in Madagascar: A Seasonal Multi-Market Model. *Journal of Policy Modeling*, 28(9), pp. 1023–1027.

Stock, J. & Watson, M. (2003). *Introduction to econometrics*. Boston: Addison Wesley.

Styger, P. & Heymans, A. (2008). Seasonality as an Unobservable Component in South African Agricultural Market Data. *International Business & Economic Research Journal*, 7(3), pp. 97–106.

Taylor, J.W. (2008). Estimating Value at Risk and Expected Shortfall Using Expectiles. *Journal of Financial Econometrics*, 6, pp. 231–252.

Thai Rice Exporters Association (2012). Rice Export Statistics Available from http://www.thairiceexporters.or.th/List_of_statistic.htm [Accessed 20 March 2012].

Tomek, W. & Peterson, H. (2001). Risk Management in Agricultural Markets: A Review. *Journal of Futures Markets*, 21(10), pp. 953–985.

Trolle, A.B. & Schwartz, E.S. (2009). Unspanned Stochastic Volatility and the Pricing of Commodity Derivatives. *Review of Financial Studies*, 22(11), pp. 4423–4461.

Turvey, C. (1999). The Essentials of Rainfall Derivatives and Insurance, Working Paper, University of Guelph WP 99/06.

Turvey, C. (2001). Weather Derivatives for Specific Event Risks in Agriculture. *Review of Agricultural Economics*, 23(2), pp. 333–351.

Turvey, C., Belltawn, B. & Kong, R. (2009). Weather Risk and the Viability of Weather Insurance in Western China. In: *Selected Paper annual conference of the American Agricultural Economics Association, Milwaukee Wisconsin, July 26-28 2009*, 70873096, pp. 1–33.

Turvey, C. & Chantarat, S. (2006). Weather-Linked Bonds, Working Paper, Cornell University.

Turvey, C., Weersink, A. & Celia Caiange, S. (2006). Pricing weather insurance with a random strike price: The Ontario ice-wine harvest. *American Journal Agricultural Economic*, 88(August), pp. 696–709.

Wang, K. & Barrett, C. (2007). Estimating the effects of exchange rate volatility on export volumes. *Journal of Agricultural and Resource Economics*, 32(2), pp. 225–255.

Wang, Y. (2005). *Alternative Measures ofVolatility in Agricultural Futures Markets, Thesis.* Thesis, The ohio State University.

Wei, S. & Zhu, Z. (2006). Commodity Convenience Yield and Risk Premium Determination: The Case of the I.S. Natural Gas Market. *Energy Economics*, 28, pp. 523–534.

Wilks, D. (1998). Multisite Generalization of a Daily Stochastic Precipitation Generation Model. *Journal of Hydrology*, 210, pp. 178–191.

Wilmott, P., Howison, S. & Dewynne, J. (1995). *The Mathematics of Financial Deriwatives: a Student Introduction.* Cambridge, UK: Cambridge University Press.

Wilmott, P. (2007). *Paul Wilmott Introduces Quantitative Finance.* Chichester: John Wiley & Sons, Inc., 2nd edition.

Wong, K., Hui, T. & Chan, C. (1992). Day-of-the-Week Effects: Evidence from Developing Stock Markets. *Applied Financial Economics*, 2, pp. 49–56.

Working, H. (1948). Theory of the Inverse Carrying Charge in Futures Markets. *Journal of Farm Economics*, 30(1), pp. 1–28.

Working, H. (1949). The Theory of Price of Storage. *The American Economic Review*, 39(Dec), pp. 1254–1262.

Yazici, M. (2008). The Exchange Rate and the Trade Balances of Turkish Agriculture, Manufacturing and Mining. *Quality and Quantity*, 42, pp. 45–52.

Yeboah, O., Shaik, S. & Allen, A. (2009). Exchange Rates Impacts on Agricultural Inputs Prices using VAR. *Journal of Agricultural and Applied Economics*, 41(02), pp. 511–520.

Zlatko, K. (2007). Forecasting Volatility:Evidence From the Macedonian Stock Exchange, Working Papar, Munich Personal RePEc Archive.

# Appendix A

# Price Risk Modelling for Agricultural Commodities - Effects of Asymmetry and Seasonality

Table A.1: First optimal seasonality volatility models for rubber

| | **Gaussian** | | **Standardised-t** | | **GED** | |
|---|---|---|---|---|---|---|
| | **Coefficient** | **S.E.** | **Coefficient** | **S.E** | **Coefficient** | **S.E** |
| $\omega$ | 0.000008 | 0.011290 | 0.000007 | 0.159313 | 0.000007 | 0.619201 |
| $\alpha_1$ | 0.080366 | 0.010345 | 0.091525 | 0.545392 | 0.088381 | 0.025926 |
| $\beta$ | 0.901705 | 0.409101 | 0.898127 | 0.402213 | 0.898837 | 0.178657 |
| $\mu$ | 0.000365 | 1.016982 | 0.000383 | 0.118127 | 0.000297 | 0.070114 |
| $\nu$ | | | 6.487063 | 0.004382 | 1.231145 | 0.037796 |
| $\alpha_2$ | - | | - | | - | |
| $\gamma_{mw1}$ | 0.000722 | 0.433212 | 0.000591 | 0.926196 | 0.000379 | 0.148062 |
| $\varphi_{mw1}$ | 0.000376 | 0.793317 | 0.000110 | 0.844398 | -0.000071 | 0.279620 |
| $\gamma_{mw2}$ | -0.000574 | 0.666866 | -0.000496 | 0.337259 | -0.000289 | 0.199883 |
| $\varphi_{mw2}$ | -0.000204 | 0.406678 | -0.000293 | 0.326455 | -0.000321 | 0.200860 |
| $\gamma_{my1}$ | 0.000692 | 0.401982 | 0.000473 | 1.347743 | 0.000256 | 0.215825 |
| $\varphi_{my1}$ | 0.000816 | 0.323209 | 0.000663 | 0.961935 | 0.000476 | 0.589347 |
| $\gamma_{my2}$ | 0.000175 | 0.235668 | 0.000129 | 0.940216 | -0.000094 | 0.171344 |
| $\varphi_{my2}$ | -0.000309 | 0.435745 | -0.000280 | 1.197645 | -0.000177 | 0.287462 |
| $\gamma_{my3}$ | 0.000453 | 0.355341 | 0.000596 | 0.514010 | 0.000179 | 0.330773 |
| $\varphi_{my3}$ | 0.001133 | 0.256831 | 0.001107 | 0.711228 | 0.000779 | 0.397526 |
| $\gamma_{my4}$ | -0.000143 | 0.087452 | -0.000033 | 0.433476 | -0.000337 | 0.453413 |
| $\varphi_{my4}$ | 0.000379 | 0.470574 | 0.000146 | 1.484779 | 0.000011 | 0.344812 |
| $\gamma_{my5}$ | 0.000661 | 0.271820 | 0.000601 | 0.909317 | 0.000398 | 0.248938 |
| $\varphi_{my5}$ | -0.000808 | 0.020503 | -0.000779 | 0.650565 | -0.000570 | 0.569787 |
| Loglikelihood | 12590.2824 | | 12668.4290 | | 12668.4290 | |
| AIC | -25172.41 | | -25323.5083 | | -25403.2049 | |

Table A.2: Second optimal seasonality volatility models for rubber

| | **Gaussian** | | **Standardised-t** | | **GED** | |
|---|---|---|---|---|---|---|
| | **Coefficient** | **S.E** | **Coefficient** | **S.E** | **Coefficient** | **S.E** |
| $\omega$ | 0.000008 | 0.102510 | 0.000008 | 0.653647 | 0.000008 | 0.029501 |
| $\alpha_1$ | 0.086300 | 0.028091 | 0.092679 | 0.013560 | 0.090548 | 0.022817 |
| $\beta$ | 0.896906 | 0.107880 | 0.895687 | 0.034426 | 0.896227 | 0.051250 |
| $\mu$ | 0.000428 | 0.102439 | 0.000490 | 0.139275 | 0.000352 | 0.104614 |
| $\nu$ | | | 5.882725 | 0.001196 | 1.179721 | 0.002581 |
| $\alpha_2$ | - | | - | | - | |
| $\gamma_{mw1}$ | 0.000774 | 2.630024 | 0.000619 | 0.242327 | 0.000375 | 0.123149 |
| $\varphi_{mw1}$ | 0.000458 | 1.114736 | 0.000154 | 0.175933 | -0.000032 | 0.068088 |
| $\gamma_{mw2}$ | -0.000550 | 0.595830 | -0.000488 | 0.994474 | -0.000257 | 0.190794 |
| $\varphi_{mw2}$ | -0.000184 | 0.932358 | -0.000298 | 0.429550 | -0.000335 | 0.190794 |
| $\gamma_{my1}$ | 0.000819 | 0.496628 | 0.000538 | 1.003210 | 0.000289 | 0.190794 |
| $\varphi_{my1}$ | 0.000733 | 0.215577 | 0.000653 | 0.165563 | 0.000411 | 0.190794 |
| $\gamma_{my2}$ | 0.000096 | 1.278326 | 0.000026 | 0.339096 | -0.000107 | 0.190794 |
| $\varphi_{my2}$ | -0.000340 | 1.279971 | -0.000313 | 0.362260 | -0.000197 | 0.190794 |
| $\gamma_{my3}$ | 0.000420 | 0.683155 | 0.000611 | 0.399844 | 0.000146 | 0.190794 |
| $\varphi_{my3}$ | 0.001051 | 1.148725 | 0.001000 | 1.042247 | 0.000657 | 0.190794 |
| $\gamma_{my4}$ | -0.000104 | 0.334468 | 0.000021 | 0.354398 | -0.000351 | 0.190794 |
| $\varphi_{my4}$ | 0.000293 | 0.900523 | 0.000096 | 0.314417 | -0.000053 | 0.190794 |
| $\gamma_{my5}$ | 0.000836 | 1.302777 | 0.000675 | 0.100200 | 0.000416 | 0.190794 |
| $\varphi_{my5}$ | -0.000856 | 0.914971 | -0.000806 | 0.278526 | -0.000579 | 0.190794 |
| Loglikelihood | 13196.5333 | | 13314.5457 | | 13365.6452 | |
| AIC | -26379.2185 | | -26612.6514 | | -26696.4867 | |

Table A.3: First optimal seasonality volatility models for white sugar

| | **Gaussian** | | **Standardised-t** | | **GED** | |
|---|---|---|---|---|---|---|
| | **Coefficient** | **S.E.** | **Coefficient** | **S.E** | **Coefficient** | **S.E** |
| $\omega$ | 0.000000 | 0.000005 | 0.000001 | 0.000258 | 0.000001 | 0.045973 |
| $\alpha_1$ | 0.271839 | 0.018255 | 0.051334 | 0.004249 | 0.050804 | 0.000336 |
| $\beta$ | 0.702975 | 0.019196 | 0.971082 | 0.008368 | 0.967948 | 0.000103 |
| $\mu$ | 0.000159 | 0.000123 | -0.000044 | 0.075502 | -0.000009 | 0.006307 |
| $\nu$ | | | 3.324388 | 0.000927 | 0.931931 | 0.000635 |
| $\alpha_2$ | -0.130278 | 0.015504 | -0.044831 | 0.004215 | -0.042379 | 0.000768 |
| $\gamma_{mw1}$ | 0.000761 | 0.000182 | 0.000948 | 0.035294 | 0.000478 | 0.009377 |
| $\varphi_{mw1}$ | -0.000537 | 0.000175 | -0.000131 | 0.097394 | -0.000027 | 0.010442 |
| $\gamma_{mw2}$ | 0.000527 | 0.000178 | 0.000109 | 0.059193 | 0.000203 | 0.008352 |
| $\varphi_{mw2}$ | 0.000107 | 0.000175 | -0.000122 | 0.001465 | -0.000011 | 0.029660 |
| $\gamma_{my1}$ | 0.000151 | 0.000162 | -0.000056 | 0.017251 | -0.000245 | 0.025150 |
| $\varphi_{my1}$ | 0.000328 | 0.000171 | 0.000349 | 0.168136 | 0.000133 | 0.011825 |
| $\gamma_{my2}$ | 0.000531 | 0.000181 | 0.000621 | 0.036735 | 0.000538 | 0.006371 |
| $\varphi_{my2}$ | -0.000970 | 0.000185 | -0.000840 | 0.107986 | -0.000402 | 0.003781 |
| $\gamma_{vw1}$ | -0.000055 | 0.000009 | | | | |
| $\varphi_{vw1}$ | 0.000015 | 0.000004 | | | | |
| $\gamma_{vw2}$ | -0.000072 | 0.000012 | | | | |
| $\varphi_{vw2}$ | -0.000036 | 0.000004 | | | | |
| $\gamma_{vy1}$ | -0.000001 | 0.000002 | | | | |
| $\varphi_{vy1}$ | -0.000008 | 0.000002 | | | | |
| $\gamma_{vy2}$ | -0.000005 | 0.000002 | | | | |
| $\varphi_{vy2}$ | -0.000001 | 0.000002 | | | | |
| Log-likelihood | 10184.0970 | | 10528.3996 | | 10534.2790 | |
| AIC | -20326.1940 | | -21012.7992 | | -21024.5579 | |

Table A.4: Second optimal seasonality volatility models for white sugar

| | **Gaussian** | | **Standardised-t** | | **GED** | |
|---|---|---|---|---|---|---|
| | **Coefficient** | **S.E** | **Coefficient** | **S.E** | **Coefficient** | **S.E** |
| $\omega$ | 0.000000 | 0.000005 | 0.000001 | 0.268763 | 0.000001 | 0.049609 |
| $\alpha_1$ | 0.230195 | 0.017867 | 0.050844 | 0.037776 | 0.054913 | 0.014055 |
| $\beta$ | 0.788314 | 0.018625 | 0.968247 | 0.023603 | 0.964574 | 0.036602 |
| $\mu$ | 0.000172 | 0.000113 | 0.000042 | 0.299942 | 0.000043 | 0.033549 |
| $\nu$ | | | 3.481626 | 0.000419 | 0.936897 | 0.023882 |
| $\alpha_2$ | -0.117754 | 0.011436 | -0.038192 | 0.025417 | -0.040428 | 0.047543 |
| $\gamma_{mw1}$ | 0.000737 | 0.000152 | 0.000912 | 0.090679 | 0.000446 | 0.062036 |
| $\varphi_{mw1}$ | -0.000587 | 0.000163 | -0.000149 | 0.058963 | -0.000022 | 0.044438 |
| $\gamma_{mw2}$ | 0.000494 | 0.000144 | 0.000122 | 0.085226 | 0.000173 | 0.050682 |
| $\varphi_{mw2}$ | 0.000149 | 0.000148 | -0.000128 | 0.060154 | -0.000005 | 0.030896 |
| $\gamma_{my1}$ | 0.000041 | 0.000159 | -0.000116 | 0.098269 | -0.000253 | 0.059968 |
| $\varphi_{my1}$ | 0.000225 | 0.000168 | 0.000254 | 0.350208 | 0.000064 | 0.024613 |
| $\gamma_{my2}$ | 0.000550 | 0.000147 | 0.000640 | 0.180703 | 0.000472 | 0.030456 |
| $\varphi_{my2}$ | -0.000907 | 0.000163 | -0.000851 | 0.133447 | -0.000438 | 0.048081 |
| $\gamma_{vw1}$ | 0.000003 | 0.000009 | | | | |
| $\varphi_{vw1}$ | 0.000027 | 0.000004 | | | | |
| $\gamma_{vw2}$ | -0.000026 | 0.000012 | | | | |
| $\varphi_{vw2}$ | -0.000040 | 0.000005 | | | | |
| $\gamma_{vy1}$ | -0.000001 | 0.000001 | | | | |
| $\varphi_{vy1}$ | -0.000006 | 0.000001 | | | | |
| $\gamma_{vy2}$ | -0.000004 | 0.000001 | | | | |
| $\varphi_{vy2}$ | 0.000000 | 0.000001 | | | | |
| Log-likelihood | 10759.3522 | | 11119.3615 | | 11129.7610 | |
| AIC | -21476.7044 | | -22194.7231 | | -22215.5221 | |

Table A.5: First optimal seasonality volatility models for rough rice

| | **Gaussian** | | **Standardised-t** | | **GED** | |
|---|---|---|---|---|---|---|
| | **Coefficient** | **S.E.** | **Coefficient** | **S.E** | **Coefficient** | **S.E** |
| $\omega$ | 0.000102 | 0.000009 | 0.000001 | 0.000006 | 0.000004 | 0.000001 |
| $\alpha$ | 0.198073 | 0.001911 | 0.055959 | 0.030084 | 0.065587 | 0.004439 |
| $\beta$ | 0.317579 | 0.000267 | 0.916547 | 0.072792 | 0.888129 | 0.003103 |
| $\mu$ | 0.000463 | 0.000156 | -0.000056 | 0.000307 | -0.000132 | 0.000093 |
| $\nu$ | | | 4.510316 | 0.097855 | 1.146417 | 0.000880 |
| $\alpha_2$ | - | | - | | - | |
| $\gamma_{mw1}$ | 0.000925 | 0.000229 | 0.000769 | 0.000326 | 0.000352 | 0.000101 |
| $\varphi_{mw1}$ | -0.000340 | 0.000259 | -0.000699 | 0.000173 | -0.000868 | 0.000192 |
| $\gamma_{mw2}$ | -0.000226 | 0.000225 | 0.000259 | 0.000308 | -0.000021 | 0.000089 |
| $\varphi_{mw2}$ | 0.000843 | 0.000256 | 0.000746 | 0.000308 | 0.000372 | 0.000250 |
| $\gamma_{my1}$ | 0.000240 | 0.000218 | 0.000590 | 0.000375 | 0.000972 | 0.000134 |
| $\varphi_{my1}$ | 0.000553 | 0.000235 | 0.000105 | 0.000205 | -0.000064 | 0.000185 |
| $\gamma_{vw1}$ | -0.000060 | 0.000040 | -0.000003 | 0.000016 | -0.000006 | 0.000004 |
| $\varphi_{vw1}$ | 0.000003 | 0.000014 | 0.000006 | 0.000003 | 0.000010 | 0.000002 |
| $\gamma_{vw2}$ | 0.000037 | 0.000008 | -0.000003 | 0.000005 | -0.000002 | 0.000003 |
| $\varphi_{vw2}$ | 0.000044 | 0.000012 | 0.000001 | 0.000018 | 0.000003 | 0.000001 |
| $\gamma_{vy1}$ | -0.000063 | 0.000036 | -0.000012 | 0.000022 | -0.000016 | 0.000001 |
| $\varphi_{vy1}$ | 0.000018 | 0.000006 | 0.000009 | 0.000014 | 0.000010 | 0.000002 |
| $\gamma_{vy2}$ | 0.000020 | 0.000026 | -0.000006 | 0.000026 | -0.000005 | 0.000001 |
| $\varphi_{vy2}$ | 0.000044 | 0.000006 | 0.000007 | 0.000008 | 0.000009 | 0.000003 |
| $\gamma_{vy3}$ | -0.000038 | 0.000030 | -0.000002 | 0.000004 | -0.000004 | 0.000003 |
| $\varphi_{vy3}$ | 0.000029 | 0.000005 | 0.000012 | 0.000034 | 0.000014 | 0.000001 |
| $\gamma_{vy4}$ | -0.000004 | 0.000006 | 0.000002 | 0.000018 | 0.000004 | 0.000003 |
| $\varphi_{vy4}$ | 0.000027 | 0.000006 | 0.000002 | 0.000015 | 0.000004 | 0.000003 |
| $\gamma_{vy5}$ | 0.000012 | 0.000006 | 0.000014 | 0.000003 | 0.000016 | 0.000002 |
| $\varphi_{vy5}$ | 0.000040 | 0.000008 | 0.000004 | 0.000008 | 0.000005 | 0.000003 |
| $\gamma_{vy6}$ | 0.000157 | 0.000028 | 0.000018 | 0.000032 | 0.000024 | 0.000001 |
| $\varphi_{vy6}$ | 0.000038 | 0.000035 | -0.000014 | 0.000023 | -0.000017 | 0.000002 |
| Log-likelihood | 6227.8146 | | 6324.3895 | | 6321.8699 | |
| AIC | -12400.6291 | | -12592.7789 | | -12587.7398 | |

Table A.6: Second optimal seasonality volatility models for rough rice

| | **Gaussian** | | **Standardised-t** | | **GED** | |
|---|---|---|---|---|---|---|
| | **Coefficient** | **S.E** | **Coefficient** | **S.E** | **Coefficient** | **S.E** |
| $\omega$ | 0.000094 | 0.000002 | 0.000000 | 0.000009 | 0.000002 | 0.000003 |
| $\alpha$ | 0.177866 | 0.000847 | 0.047985 | 0.006172 | 0.054951 | 0.005161 |
| $\beta$ | 0.364885 | 0.000507 | 0.928803 | 0.027545 | 0.907303 | 0.005686 |
| $\mu$ | 0.000459 | 0.000140 | -0.000077 | 0.000136 | -0.000054 | 0.000091 |
| $\nu$ | | | 4.863816 | 0.003652 | 1.186077 | 0.001283 |
| $\alpha_2$ | - | | - | | - | |
| $\gamma_{mw1}$ | 0.001228 | 0.000199 | 0.000982 | 0.000205 | 0.000278 | 0.000097 |
| $\varphi_{mw1}$ | -0.000170 | 0.000199 | -0.000559 | 0.000177 | -0.000326 | 0.000115 |
| $\gamma_{mw2}$ | -0.000186 | 0.000156 | 0.000260 | 0.000194 | 0.000398 | 0.000115 |
| $\varphi_{mw2}$ | 0.000751 | 0.000197 | 0.000641 | 0.000191 | 0.000337 | 0.000086 |
| $\gamma_{my1}$ | 0.000148 | 0.000213 | 0.000465 | 0.000181 | 0.000596 | 0.000084 |
| $\varphi_{my1}$ | 0.000089 | 0.000207 | -0.000267 | 0.000200 | -0.000426 | 0.000165 |
| $\gamma_{vw1}$ | -0.000070 | 0.000003 | -0.000006 | 0.000001 | -0.000006 | 0.000073 |
| $\varphi_{vw1}$ | 0.000010 | 0.000003 | 0.000006 | 0.000001 | 0.000010 | 0.000056 |
| $\gamma_{vw2}$ | 0.000020 | 0.000003 | -0.000001 | 0.000001 | 0.000001 | 0.000099 |
| $\varphi_{vw2}$ | 0.000047 | 0.000002 | -0.000002 | 0.000001 | 0.000002 | 0.000075 |
| $\gamma_{vy1}$ | -0.000059 | 0.000002 | -0.000009 | 0.000001 | -0.000013 | 0.000146 |
| $\varphi_{vy1}$ | 0.000025 | 0.000001 | 0.000007 | 0.000001 | 0.000008 | 0.000036 |
| $\gamma_{vy2}$ | 0.000026 | 0.000002 | -0.000003 | 0.000002 | -0.000003 | 0.000137 |
| $\varphi_{vy2}$ | 0.000021 | 0.000003 | 0.000005 | 0.000002 | 0.000006 | 0.000055 |
| $\gamma_{vy3}$ | -0.000034 | 0.000002 | -0.000001 | 0.000001 | -0.000003 | 0.000053 |
| $\varphi_{vy3}$ | 0.000040 | 0.000003 | 0.000011 | 0.000001 | 0.000013 | 0.000097 |
| $\gamma_{vy4}$ | -0.000015 | 0.000002 | 0.000001 | 0.000001 | 0.000002 | 0.000078 |
| $\varphi_{vy4}$ | 0.000011 | 0.000002 | 0.000001 | 0.000002 | 0.000004 | 0.000083 |
| $\gamma_{vy5}$ | 0.000024 | 0.000002 | 0.000011 | 0.000001 | 0.000013 | 0.000062 |
| $\varphi_{vy5}$ | 0.000045 | 0.000002 | 0.000002 | 0.000001 | 0.000004 | 0.000100 |
| $\gamma_{vy6}$ | 0.000137 | 0.000002 | 0.000015 | 0.000002 | 0.000021 | 0.000049 |
| $\varphi_{vy6}$ | 0.000024 | 0.000002 | -0.000012 | 0.000001 | -0.000015 | 0.000081 |
| Log-likelihood | 6927.4604 | | 7017.3241 | | 7014.5731 | |
| AIC | -13800.9208 | | -13978.8270 | | -13973.1462 | |

Table A.7: The out-of-sample backtesting results of rubber VaR estimation with GARCH

| Rubber | | GARCH (Gaussian) | | | | GARCH (GED) | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | **90%** | **95%** | **99%** | **99.50%** | **90%** | **95%** | **99%** | **99.50%** |
| **one-day VaR** | **No. of Hit** | 49 | 28 | 16 | 11 | 52 | 27 | 9 | 7 |
| | **Hit Percentage** | 9.42% | 5.38% | 3.08% | 2.12% | 10.00% | 5.19% | 1.73% | 1.35% |
| | **Failure test** | 0.3638 | 0.7004 | 1.0000 | 1.0000 | 0.5368 | 0.6290 | 0.9611 | 0.9948 |
| | **P Value** | 0.3638 | 0.2996 | 0.0000 | 0.0000 | 0.4632 | 0.3710 | 0.0389 | 0.0052 |
| | **DQ** | 24.3553 | 25.3250 | 45.5039 | 41.2995 | 22.3018 | 25.9042 | 12.7339 | 8.6944 |
| | **P Value** | 0.0004 | 0.0003 | 0.0000 | 0.0000 | 0.0011 | 0.0002 | 0.0475 | 0.1915 |
| **5-Day VaR** | **No. of Hit** | 13 | 5 | 3 | 3 | 14 | 5 | 3 | 3 |
| | **Hit Percentage** | 12.75% | 4.90% | 2.94% | 2.94% | 13.73% | 4.90% | 2.94% | 2.94% |
| | **Failure test** | 0.8610 | 0.5980 | 0.9804 | 0.9982 | 0.9169 | 0.5980 | 0.9804 | 0.9982 |
| | **P Value** | 0.1390 | 0.4020 | 0.0196 | 0.0018 | 0.0831 | 0.4020 | 0.0196 | 0.0018 |
| | **DQ** | 12.7207 | 4.4717 | 5.1251 | 16.7160 | 11.5785 | 4.6122 | 5.1183 | 7.2374 |
| | **P Value** | 0.0477 | 0.6131 | 0.5279 | 0.0104 | 0.0721 | 0.5944 | 0.5287 | 0.2994 |

Table A.8: The out-of-sample backtesting results of sugar VaR estimation with GARCH

| Sugar | | GARCH (Gaussian) | | | | GARCH (GED) | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | **90%** | **95%** | **99%** | **99.50%** | **90%** | **95%** | **99%** | **99.50%** |
| **one-day VaR** | **No. of Hit** | 64 | 42 | 13 | 8 | 62 | 35 | 7 | 6 |
| | **Hit Percentage** | 12.31% | 8.08% | 2.50% | 1.54% | 11.92% | 6.73% | 1.35% | 1.15% |
| | **Failure test** | 0.9630 | 0.9990 | 0.9991 | 0.9986 | 0.9346 | 0.9674 | 0.8459 | 0.9831 |
| | **P Value** | 0.0370 | 0.0010 | 0.0009 | 0.0014 | 0.0654 | 0.0326 | 0.1541 | 0.0169 |
| | **DQ** | 79.6454 | 31.0110 | 47.7535 | 17.1729 | 70.0449 | 30.2196 | 3.0100 | 7.4131 |
| | **P Value** | 0.0000 | 0.0000 | 0.0000 | 0.0087 | 0.0000 | 0.0000 | 0.8076 | 0.2843 |
| **5-Day VaR** | **No. of Hit** | 16 | 4 | 1 | 1 | 15 | 3 | 1 | 1 |
| | **Hit Percentage** | 15.69% | 3.92% | 0.98% | 0.98% | 14.71% | 2.94% | 0.98% | 0.98% |
| | **Failure test** | 0.9754 | 0.4183 | 0.7284 | 0.9071 | 0.9534 | 0.2440 | 0.7284 | 0.9071 |
| | **P Value** | 0.0246 | 0.4183 | 0.2716 | 0.0929 | 0.0466 | 0.2440 | 0.2716 | 0.0929 |
| | **DQ** | 11.4719 | 4.5699 | 2.0949 | 3.6619 | 8.1784 | 1.4205 | 2.8442 | 6.2127 |
| | **P Value** | 0.0748 | 0.6000 | 0.9108 | 0.7223 | 0.2253 | 0.9646 | 0.8281 | 0.3998 |

Table A.9: The out-of-sample backtesting results of rough rice VaR estimation with GARCH .

| Rough Rice | | GARCH (Gaussian) | | | | GARCH (Standardised-t) | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | **90%** | **95%** | **99%** | **99.50%** | **90%** | **95%** | **99%** | **99.50%** |
| **one-day VaR** | **No. of Hit** | 56 | 36 | 10 | 4 | 65 | 33 | 5 | 3 |
| | **Hit Percentage** | 10.77% | 6.92% | 1.92% | 0.77% | 12.50% | 6.35% | 0.96% | 0.58% |
| | **Failure test** | 0.7482 | 0.9786 | 0.9828 | 0.8779 | 0.9728 | 0.9301 | 0.5807 | 0.7362 |
| | **P Value** | 0.2518 | 0.0214 | 0.0172 | 0.1221 | 0.0272 | 0.0699 | 0.4193 | 0.2638 |
| | **DQ** | 4.6443 | 7.2769 | 41.2667 | 17.5186 | 6.0219 | 16.3949 | 19.4018 | 1.1488 |
| | **P Value** | 0.5902 | 0.2960 | 0.0000 | 0.0076 | 0.4207 | 0.0118 | 0.0035 | 0.9793 |
| **5-Day VaR** | **No. of Hit (5-Day VaR)** | 13 | 4 | 0 | 0 | 18 | 6 | 0 | 0 |
| | **Hit Percentage** | 12.75% | 3.92% | 0.00% | 0.00% | 17.65% | 5.88% | 0.00% | 0.00% |
| | **Failure test** | 0.8610 | 0.4183 | 0.3587 | 0.5997 | 0.9943 | 0.7509 | 0.3587 | 0.5997 |
| | **P Value** | 0.1390 | 0.4183 | 0.3587 | 0.4003 | 0.0057 | 0.2491 | 0.3587 | 0.4003 |
| | **DQ** | 18.4796 | 9.2863 | N/A | N/A | 17.8497 | 14.0863 | N/A | N/A |
| | **P Value** | 0.0051 | 0.1581 | N/A | N/A | 0.0066 | 0.0287 | N/A | N/A |

Table A.10: The out-of-sample backtesting results of rubber VaR estimation with Seasonal-GARCH

| Rubber | | Seasonal-GARCH (Gaussian) | | | | Seasonal-GARCH (GED) | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | **90%** | **95%** | **99%** | **99.50%** | **90%** | **95%** | **99%** | **99.50%** |
| **one-day VaR** | **No. of Hit** | 49 | 27 | 15 | 12 | 52 | 27 | 10 | 7 |
| | **Hit Percentage** | 9.42% | 5.19% | 2.88% | 2.31% | 10.00% | 5.19% | 1.92% | 1.35% |
| | **Failure test** | 0.3638 | 0.6290 | 0.9999 | 1.0000 | 0.5368 | 0.6290 | 0.9828 | 0.9948 |
| | **P Value** | 0.3638 | 0.3710 | 0.0001 | 0.0000 | 0.4632 | 0.3710 | 0.0172 | 0.0052 |
| | **DQ** | 24.0754 | 25.5456 | 40.8183 | 53.5344 | 22.0112 | 25.7491 | 12.6701 | 13.3204 |
| | **P Value** | 0.0005 | 0.0003 | 0.0000 | 0.0000 | 0.0012 | 0.0002 | 0.0486 | 0.0382 |
| **5-Day VaR** | **No. of Hit** | 11 | 6 | 3 | 3 | 11 | 6 | 3 | 3 |
| | **Hit Percentage** | 10.78% | 5.88% | 2.94% | 2.94% | 10.00% | 5.58% | 2.12% | 1.54% |
| | **Failure test** | 0.6789 | 0.7509 | 0.9804 | 0.9982 | 0.6789 | 0.7509 | 0.9804 | 0.9982 |
| | **P Value** | 0.3211 | 0.2491 | 0.0196 | 0.0018 | 0.3211 | 0.2491 | 0.0196 | 0.0018 |
| | **DQ** | 18.6584 | 3.4127 | 5.2872 | 5.2872 | 18.5309 | 3.4469 | 5.3040 | 15.0694 |
| | **P Value** | 0.0048 | 0.7555 | 0.5075 | 0.5075 | 0.0050 | 0.7510 | 0.5055 | 0.0197 |

Table A.11: The out-of-sample backtesting results of sugar VaR estimation with Seasonal-GARCH

| Sugar | | Seasonal-GARCH (Gaussian) | | | | Seasonal-GARCH (GED) | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | **90%** | **95%** | **99%** | **99.50%** | **90%** | **95%** | **99%** | **99.50%** |
| **one-day VaR** | **No. of Hit** | 59 | 41 | 18 | 14 | 67 | 38 | 13 | 10 |
| | **Hit Percentage** | 11.35% | 7.88% | 3.46% | 2.69% | 12.88% | 7.31% | 2.50% | 1.92% |
| | **Failure test** | 0.8629 | 0.9982 | 1.0000 | 1.0000 | 0.9859 | 0.9914 | 0.9991 | 0.9999 |
| | **P Value** | 0.1371 | 0.0018 | 0.0000 | 0.0000 | 0.0141 | 0.0086 | 0.0009 | 0.0001 |
| | **DQ** | 15.5845 | 27.6621 | 128.1860 | 70.6344 | 19.0533 | 42.3398 | 23.3756 | 16.0750 |
| | **P Value** | 0.0162 | 0.0001 | 0.0000 | 0.0000 | 0.0041 | 0.0000 | 0.0007 | 0.0134 |
| **5-Day VaR** | **No. of Hit** | 16 | 10 | 3 | 1 | 18 | 8 | 1 | 1 |
| | **Hit Percentage** | 15.69% | 9.80% | 2.94% | 0.98% | 17.65% | 7.84% | 0.98% | 0.98% |
| | **Failure test** | 0.9754 | 0.9868 | 0.9804 | 0.9071 | 0.9943 | 0.9303 | 0.7284 | 0.9071 |
| | **P Value** | 0.0246 | 0.0132 | 0.0196 | 0.0929 | 0.0057 | 0.0697 | 0.2716 | 0.0929 |
| | **DQ** | 11.2947 | 15.9309 | 7.5411 | 6.8483 | 20.0586 | 15.8806 | 3.4383 | 7.4058 |
| | **P Value** | 0.0797 | 0.0141 | 0.2737 | 0.3351 | 0.0027 | 0.0144 | 0.7522 | 0.2849 |

Table A.12: The out-of-sample backtesting results of rough rice VaR estimation with Seasonal-GARCH

| Rough Rice | | Seasonal-GARCH (Gaussian) | | | | Seasonal-GARCH (Standardised-t) | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | **90%** | **95%** | **99%** | **99.50%** | **90%** | **95%** | **99%** | **99.50%** |
| **one-day VaR** | **No. of Hit** | 44 | 29 | 3 | 2 | 59 | 30 | 3 | 0 |
| | **Hit Percentage** | 8.46% | 5.58% | 0.58% | 0.38% | 11.35% | 5.77% | 0.58% | 0.00% |
| | **Failure test** | 0.1354 | 0.7641 | 0.2366 | 0.5181 | 0.8629 | 0.8191 | 0.2366 | 0.0738 |
| | **P Value** | 0.1354 | 0.2359 | 0.2366 | 0.4819 | 0.1371 | 0.1809 | 0.2366 | 0.0738 |
| | **DQ** | 4.7982 | 5.7129 | 3.0960 | 1.8449 | 6.8455 | 11.0529 | 7.0272 | N/A |
| | **P Value** | 0.5699 | 0.4561 | 0.7967 | 0.9334 | 0.3354 | 0.0868 | 0.3183 | N/A |
| **5-Day VaR** | **No. of Hit (5-Day VaR)** | 19 | 10 | 0 | 0 | 19 | 9 | 0 | 0 |
| | **Hit Percentage** | 18.63% | 9.80% | 0.00% | 0.00% | 18.63% | 8.82% | 0.00% | 0.00% |
| | **Failure test** | 0.9975 | 0.9868 | 0.3587 | 0.5997 | 0.9975 | 0.9682 | 0.3587 | 0.5997 |
| | **P Value** | 0.0025 | 0.0132 | 0.3587 | 0.4003 | 0.0025 | 0.0318 | 0.3587 | 0.4003 |
| | **DQ** | 19.6497 | 13.5496 | N/A | N/A | 17.1865 | 17.7160 | N/A | N/A |
| | **P Value** | 0.0032 | 0.0351 | N/A | N/A | 0.0086 | 0.0070 | N/A | N/A |

Figure A.1: The Comparison of rubber VaR with GARCH and Seasonal Volatility at 99% confidential level and the actual return over 2011 to 2012

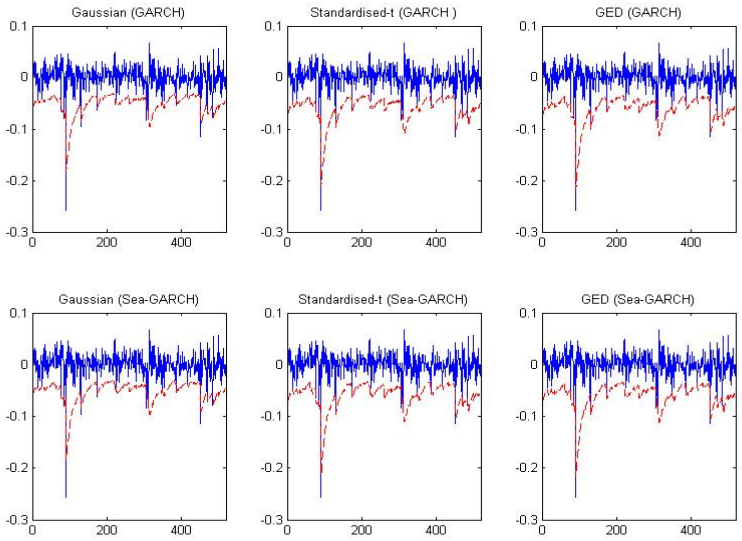



Figure A.2: The Comparison of white sugar VaR with GARCH and Seasonal Volatility at 99% confidential level and the actual return over 2011 to 2012

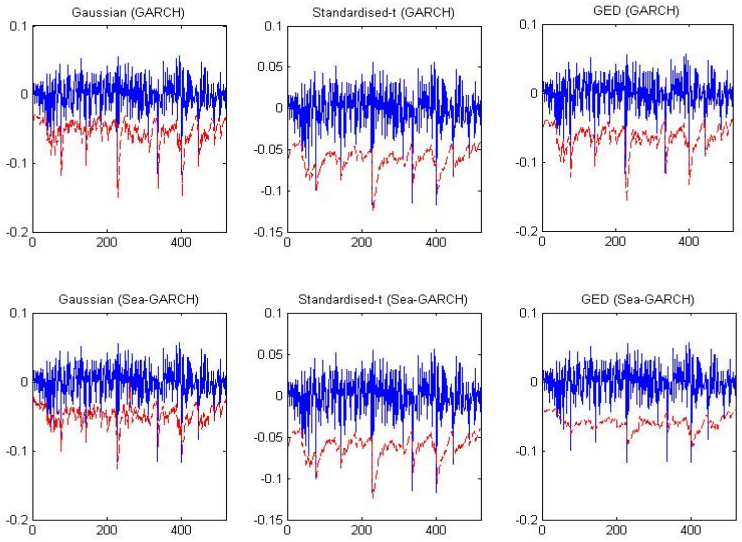
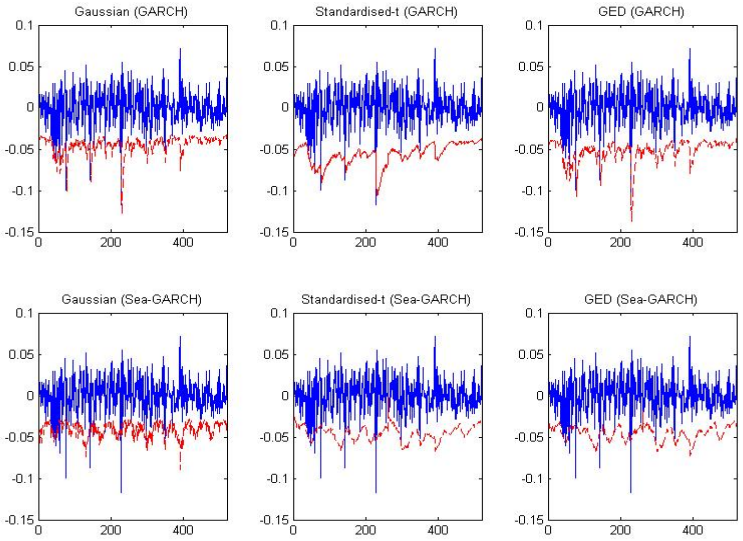


Figure A.3: The Comparison of rough rice VaR with GARCH and Seasonal Volatility at 99% confidential level and the actual return over 2011 to 2012



# Appendix B

# Modelling Convenience Yield for Agricultural Commodities

Table B.1: The estimations of corn net conveience yield with Gaussian and Standardised-t error distributions

| | 2nd Contract | | | 4th Contract | | | 6th Contract | | |
|---|---|---|---|---|---|---|---|---|---|
| GARCH | Coefficient | S.E. | t-Statistic | Coefficient | S.E. | t-Statistic | Coefficient | S.E. | t-Statistic |
| $\omega$ | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 6.9112 | 0.0000 | 0.0000 | 3.1832 |
| $\alpha$ | 0.0160 | 0.0004 | 42.4030 | 0.5080 | 0.0010 | 531.9563 | 0.1281 | 0.0013 | 97.5792 |
| $\beta_1$ | 0.9840 | 0.0004 | 2777.7679 | 0.1470 | 0.0006 | 250.1796 | 0.2769 | 0.0000 | 490.0636 |
| $\mu$ | 0.0000 | 0.0000 | 9.2900 | 0.0000 | 0.0000 | 15.2592 | 0.0000 | 0.0000 | 5.9865 |
| $\beta_2$ | 0.0028 | 0.0005 | 5.3961 | -0.0555 | 0.0010 | -55.6810 | -0.0043 | 0.0005 | -7.9610 |
| MLE | 45913.5515 | | | 46227.6938 | | | 47215.3355 | | |
| $\omega$ | 0.0000 | 0.0000 | 4.1141 | 0.0000 | 0.0000 | 4.4266 | 0.0000 | 0.0000 | 2.7392 |
| $\alpha$ | 0.2316 | 0.0002 | 972.9710 | 0.8528 | 0.0002 | 448.4106 | 0.1377 | 0.0000 | 429.3122 |
| $\beta_1$ | 0.5631 | 0.0008 | 673.0949 | 0.1405 | 0.0002 | 746.9815 | 0.3042 | 0.0004 | 697.1890 |
| $\mu$ | 0.0000 | 0.0000 | -29.3224 | 0.0000 | 0.0000 | -33.7515 | 0.0000 | 0.0000 | -17.6052 |
| $\beta_2$ | 0.0121 | 0.0005 | 22.7771 | 0.0010 | 0.0004 | 2.4896 | -0.0009 | 0.0003 | -2.6487 |
| $\nu$ | 2.4916 | 0.0020 | 1234.3618 | 2.6416 | 0.0022 | 1177.2130 | 2.8520 | 0.0014 | 1999.3607 |
| MLE | 47058.8511 | | | 48714.1924 | | | 49303.3405 | | |
| Likelihood Ratio test | 2290.5992 | | | 4972.9972 | | | 4176.0100 | | |
| IGARCH | | | | | | | | | |
| $\omega$ | 0.0000 | 0.0000 | 1.5355 | 0.0000 | 0.0000 | 1.5991 | 0.0000 | 0.0000 | 0.0000 |
| $\beta_1$ | 0.5312 | 0.0004 | 1270.1082 | 0.3704 | 0.0001 | 4515.3899 | 0.9830 | 0.0003 | 367.0807 |
| $\mu$ | 0.0000 | 0.0000 | -29.5161 | 0.0000 | 0.0000 | 10.2368 | 0.0000 | 0.0000 | 9.1729 |
| $\beta_2$ | -0.1062 | 0.0008 | -131.3105 | -0.0086 | 0.0009 | -9.4273 | -0.0047 | 0.0007 | -6.7194 |
| MLE | 44173.5681 | | | 45702.0350 | | | 46895.1147 | | |
| $\omega$ | 0.0000 | 0.0000 | 1.6193 | 0.0000 | 0.0000 | 4.7290 | 0.0000 | 0.0000 | 0.0000 |
| $\beta_1$ | 0.3177 | 0.0004 | 857.2820 | 0.3082 | 0.0002 | 189.0619 | 0.9638 | 0.0002 | 459.5138 |
| $\mu$ | 0.0000 | 0.0000 | -20.9566 | 0.0000 | 0.0000 | -31.7284 | 0.0000 | 0.0000 | -20.1568 |
| $\beta_2$ | 0.0088 | 0.0008 | 10.9057 | -0.0007 | 0.0005 | -1.3641 | -0.0010 | 0.0004 | -2.8670 |
| $\nu$ | 2.9102 | 0.0014 | 2149.1913 | 2.5650 | 0.0013 | 1986.6860 | 2.5306 | 0.0010 | 2559.8759 |
| MLE | 47000.2943 | | | 48596.3622 | | | 49104.6064 | | |
| Likelihood Ratio test | 5653.4524 | | | 5788.6544 | | | 4418.9834 | | |
| Likelihood Ratio test (GARCH and IGARCH) | 117.1136 | | | 235.6604 | | | 397.4682 | | |

Table B.2: The estimations of cotton net conveience yield with Gaussian and Standardised-t error distributions

| | 2nd Contract | | | 4th Contract | | | 6th Contract | | |
|---|---|---|---|---|---|---|---|---|---|
| GARCH | Coefficient | S.E. | t-Statistic | Coefficient | S.E. | t-Statistic | Coefficient | S.E. | t-Statistic |
| $\omega$ | 0.0000 | 0.0000 | 6.8858 | 0.0000 | 0.0000 | 0.9664 | 0.0000 | 0.0000 | 1.1659 |
| $\alpha$ | 0.4150 | 0.0018 | 227.8868 | 0.7161 | 0.0033 | 216.4663 | 0.2740 | 0.0001 | 4703.3305 |
| $\beta_1$ | 0.0032 | 0.0018 | 1.8078 | 0.1656 | 0.0040 | 41.0230 | 0.0029 | 0.0013 | 2.1932 |
| $\mu$ | 0.0000 | 0.0000 | -4.5150 | 0.0000 | 0.0000 | 0.3787 | 0.0000 | 0.0000 | 7.2222 |
| $\beta_2$ | -0.0790 | 0.0018 | -43.4535 | -0.0142 | 0.0009 | -16.5944 | -0.0058 | 0.0005 | -12.1125 |
| MLE | 41214.5499 | | | 44919.6997 | | | 46443.8767 | | |
| $\omega$ | 0.0000 | 0.0000 | 4.9920 | 0.0000 | 0.0000 | 6.7640 | 0.0000 | 0.0000 | 7.0064 |
| $\alpha$ | 0.7721 | 0.0008 | 963.7937 | 0.5685 | 0.0014 | 399.5327 | 0.5521 | 0.0003 | 1629.5434 |
| $\beta_1$ | 0.2334 | 0.0055 | 42.2431 | 0.2180 | 0.0006 | 370.8187 | 0.0813 | 0.0000 | 56456.2325 |
| $\mu$ | 0.0000 | 0.0000 | -22.9499 | 0.0000 | 0.0000 | -20.0691 | 0.0000 | 0.0000 | -14.7800 |
| $\beta_2$ | 0.0086 | 0.0007 | 11.7513 | 0.0024 | 0.0005 | 4.7397 | 0.0005 | 0.0004 | 1.3383 |
| $\nu$ | 2.5124 | 0.0016 | 1566.6206 | 2.8114 | 0.0019 | 1459.9918 | 3.0339 | 0.0014 | 2099.4515 |
| MLE | 44151.6009 | | | 46466.5050 | | | 47717.9418 | | |
| Likelihood Ratio test | 5874.1020 | | | 3093.6106 | | | 2548.1302 | | |
| IGARCH | | | | | | | | | |
| $\omega$ | 0.0000 | 0.0000 | 0.6765 | 0.0000 | 0.0000 | 0.1220 | 0.0000 | 0.0000 | 0.1999 |
| $\beta_1$ | 0.0035 | 0.0004 | 9.3491 | 0.1829 | 0.0007 | 275.2653 | 0.9088 | 0.0000 | 18685.6949 |
| $\mu$ | 0.0000 | 0.0000 | 9.4876 | 0.0000 | 0.0000 | 8.3827 | 0.0000 | 0.0000 | 21.7859 |
| $\beta_2$ | 0.1290 | 0.0008 | 159.1083 | -0.0177 | 0.0004 | -49.9641 | -0.0019 | 0.0005 | -4.1095 |
| MLE | 40391.4612 | | | 44187.4855 | | | 46099.2233 | | |
| $\omega$ | 0.0000 | 0.0000 | 12.6328 | 0.0000 | 0.0000 | 0.2000 | 0.0000 | 0.0000 | 0.2273 |
| $\beta_1$ | 0.0092 | 0.0019 | 4.9685 | 0.1861 | 0.0000 | 4914.7692 | 0.9093 | 0.0001 | 6836.8257 |
| $\mu$ | 0.0000 | 0.0000 | -21.9102 | 0.0000 | 0.0000 | -21.3404 | 0.0000 | 0.0000 | -14.7390 |
| $\beta_2$ | 0.0075 | 0.0008 | 9.8542 | 0.0018 | 0.0000 | 75.7131 | 0.0003 | 0.0004 | 0.7950 |
| $\nu$ | 2.3824 | 0.0005 | 5247.7107 | 3.0123 | 0.0005 | 5543.2275 | 2.7522 | 0.0006 | 4243.9155 |
| MLE | 44085.6201 | | | 46308.2776 | | | 47572.7745 | | |
| Likelihood Ratio test | 7388.3178 | | | 4241.5842 | | | 2947.1023 | | |
| Likelihood Ratio test (GARCH and IGARCH) | 131.9616 | | | 316.4548 | | | 290.3347 | | |

Table B.3: The estimations of rough rice net conveience yield with Gaussian and Standardised-t error distributions

| | 2nd Contract | | | 4th Contract | | | 6th Contract | | |
|---|---|---|---|---|---|---|---|---|---|
| GARCH | Coefficient | S.E. | t-Statistic | Coefficient | S.E. | t-Statistic | Coefficient | S.E. | t-Statistic |
| $\omega$ | 0.0000 | 0.0000 | 5.4651 | 0.0000 | 0.0000 | 4.4423 | 0.0000 | 0.0000 | 6.8323 |
| $\alpha$ | 0.8490 | 0.0008 | 1003.8450 | 0.5664 | 0.0010 | 589.3789 | 0.3699 | 0.0019 | 194.0482 |
| $\beta_1$ | 0.0000 | 0.0008 | 0.0000 | 0.0187 | 0.0002 | 88.6262 | 0.0187 | 0.0006 | 33.7120 |
| $\mu$ | 0.0000 | 0.0000 | -36.9758 | 0.0000 | 0.0000 | 8.8585 | 0.0000 | 0.0000 | 5.2365 |
| $\beta_2$ | -0.0635 | 0.0008 | -75.8519 | -0.0121 | 0.0009 | -13.8360 | -0.0077 | 0.0007 | -11.6502 |
| MLE | 41887.7408 | | | 43402.7877 | | | 44555.6274 | | |
| $\omega$ | 0.0000 | 0.0000 | 0.0005 | 0.0000 | 0.0000 | 7.6890 | 0.0000 | 0.0000 | 10.1187 |
| $\alpha$ | 0.8497 | 0.0156 | 54.2993 | 0.3441 | 0.0005 | 638.1588 | 0.3632 | 0.0002 | 2372.5328 |
| $\beta_1$ | 0.0000 | 0.5000 | 0.0000 | 0.6602 | 0.0004 | 1799.3280 | 0.2434 | 0.0004 | 541.3742 |
| $\mu$ | 0.0000 | 0.0000 | -0.1302 | 0.0000 | 0.0000 | -18.4139 | 0.0000 | 0.0000 | -10.7071 |
| $\beta_2$ | 0.0055 | 0.1299 | 0.0420 | 0.0003 | 0.0005 | 0.4839 | -0.0005 | 0.0004 | -1.2233 |
| $\nu$ | 2.9990 | 0.0039 | 776.9136 | 2.4129 | 0.0015 | 1606.7747 | 2.6193 | 0.0018 | 1478.3688 |
| MLE | 43880.8445 | | | 45947.1595 | | | 46206.2134 | | |
| Likelihood Ratio test | 3986.2074 | | | 5088.7436 | | | 3301.1720 | | |
| IGARCH | | | | | | | | | |
| $\omega$ | 0.0000 | 0.0000 | 2.7798 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| $\beta_1$ | 0.6824 | 0.0013 | 517.3049 | 0.9863 | 0.0007 | 1467.4893 | 0.9743 | 0.0009 | 1030.9517 |
| $\mu$ | 0.0000 | 0.0000 | 22.8467 | 0.0000 | 0.0000 | -0.2045 | 0.0000 | 0.0000 | 7.4113 |
| $\beta_2$ | 0.0826 | 0.0008 | 104.8555 | -0.0241 | 0.0007 | -33.7277 | -0.0082 | 0.0008 | -9.7843 |
| MLE | 41585.8505 | | | 43079.6817 | | | 44507.2045 | | |
| $\omega$ | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| $\beta_1$ | 0.6779 | 0.0017 | 402.6805 | 0.9677 | 0.0001 | 19097.9226 | 0.9475 | 0.0000 | 127276.2695 |
| $\mu$ | 0.0000 | 0.0000 | -16.9571 | 0.0000 | 0.0000 | -16.8394 | 0.0000 | 0.0000 | -10.9236 |
| $\beta_2$ | 0.0014 | 0.0012 | 1.1648 | 0.0004 | 0.0006 | 0.6804 | -0.0006 | 0.0004 | -1.3640 |
| $\nu$ | 3.4312 | 0.0020 | 1733.2927 | 2.4118 | 0.0006 | 4328.7995 | 2.8574 | 0.0004 | 6884.4841 |
| MLE | 43728.4308 | | | 45845.1784 | | | 46134.4713 | | |
| Likelihood Ratio test | 4285.1606 | | | 5530.9933 | | | 3254.5336 | | |
| Likelihood Ratio test (GARCH and IGARCH) | 304.8274 | | | 203.9623 | | | 143.4842 | | |

Table B.4: The estimations of rubber net conveience yield contract with Gaussian and Standardised-t error distributions

| | 2nd Contract | | | 4th Contract | | | 6th Contract | | |
|---|---|---|---|---|---|---|---|---|---|
| GARCH | Coefficient | S.E. | t-Statistic | Coefficient | S.E. | t-Statistic | Coefficient | S.E. | t-Statistic |
| $\omega$ | 0.0000 | 0.0000 | 14.2885 | 0.0000 | 0.0000 | 14.5062 | 0.0000 | 0.0000 | 0.0022 |
| $\alpha$ | 0.5248 | 0.0054 | 97.3168 | 0.6695 | 0.0028 | 242.8178 | 0.0995 | 0.0003 | 327.2653 |
| $\beta_1$ | 0.4630 | 0.0082 | 56.5567 | 0.0166 | 0.0048 | 3.4632 | 0.8905 | 0.0011 | 826.5021 |
| $\mu$ | 0.0000 | 0.0000 | -17.4801 | 0.0000 | 0.0000 | -26.5735 | 0.0000 | 0.0000 | -8.0126 |
| $\beta_2$ | -0.1685 | 0.0038 | -44.1724 | -0.0980 | 0.0018 | -55.5985 | -0.0554 | 0.0003 | -158.7701 |
| MLE | 34107.7027 | | | 37782.4790 | | | 39652.3913 | | |
| $\omega$ | 0.0000 | 0.0000 | 19.6523 | 0.0000 | 0.0000 | 6.2172 | 0.0000 | 0.0000 | 0.0084 |
| $\alpha$ | 0.5237 | 0.0010 | 540.2858 | 0.5044 | 0.0013 | 400.0776 | 0.0674 | 0.0007 | 96.1333 |
| $\beta_1$ | 0.4391 | 0.0019 | 232.4598 | 0.3473 | 0.0058 | 59.4094 | 0.9242 | 0.0006 | 1636.2879 |
| $\mu$ | 0.0000 | 0.0000 | -14.0156 | 0.0000 | 0.0000 | -3.6100 | 0.0000 | 0.0000 | 0.5679 |
| $\beta_2$ | -0.0898 | 0.0036 | -24.8840 | -0.0161 | 0.0018 | -8.8969 | -0.0023 | 0.0001 | -26.1646 |
| $\nu$ | 4.1315 | 0.0040 | 1041.7269 | 5.7134 | 0.0024 | 2406.1335 | 3.5447 | 0.0008 | 4193.6857 |
| MLE | 34678.3979 | | | 38636.1755 | | | 40535.9592 | | |
| Likelihood Ratio test | 1141.3904 | | | 1707.3930 | | | 1767.1358 | | |
| IGARCH | | | | | | | | | |
| $\omega$ | 0.0000 | 0.0000 | 11.5742 | 0.0000 | 0.0000 | 13.5219 | 0.0000 | 0.0000 | 14.4904 |
| $\beta_1$ | 0.2696 | 0.0003 | 1035.4535 | 0.5039 | 0.0001 | 8886.6926 | 0.5155 | 0.0001 | 6919.8915 |
| $\mu$ | 0.0000 | 0.0000 | -17.6377 | 0.0000 | 0.0000 | -13.0222 | 0.0000 | 0.0000 | -6.8065 |
| $\beta_2$ | -0.1580 | 0.0033 | -48.2483 | -0.0538 | 0.0016 | -33.4670 | -0.0309 | 0.0014 | -22.6094 |
| MLE | 34083.2851 | | | 37621.5037 | | | 39518.8837 | | |
| $\omega$ | 0.0000 | 0.0000 | 17.5905 | 0.0000 | 0.0000 | 9.9765 | 0.0007 | 0.0000 | 15.1401 |
| $\beta_1$ | 0.4937 | 0.0020 | 241.3339 | 0.6899 | 0.0004 | 1753.6684 | 0.8208 | 0.0012 | 705.7904 |
| $\mu$ | 0.0000 | 0.0000 | -13.7694 | 0.0000 | 0.0000 | -3.8834 | 0.0000 | 0.0000 | 1.3279 |
| $\beta_2$ | -0.0915 | 0.0036 | -25.3814 | -0.0179 | 0.0018 | -10.0686 | -0.0020 | 0.0012 | -1.6502 |
| $\nu$ | 3.8708 | 0.0044 | 879.1209 | 3.8633 | 0.0008 | 4552.4301 | 2.1584 | 0.0010 | 2136.9548 |
| MLE | 34672.0806 | | | 38626.5385 | | | 40515.8252 | | |
| Likelihood Ratio test | 1177.5910 | | | 2010.0696 | | | 1993.8830 | | |
| Likelihood Ratio test (GARCH and IGARCH) | 12.6346 | | | 19.2740 | | | 40.2680 | | |

Table B.5: The estimations of white sugar net conveience yield with Gaussian and Standardised-t error distributions

| | 2nd Contract | | | 4th Contract | | | 6th Contract | | |
|---|---|---|---|---|---|---|---|---|---|
| GARCH | Coefficient | S.E. | t-Statistic | Coefficient | S.E. | t-Statistic | Coefficient | S.E. | t-Statistic |
| $\omega$ | 0.0000 | 0.0000 | 8.9364 | 0.0000 | 0.0000 | 1.4668 | 0.0000 | 0.0000 | 1.8357 |
| $\alpha$ | 0.9596 | 0.0003 | 2772.3555 | 0.2270 | 0.0015 | 146.8983 | 0.9831 | 0.0001 | 7434.6152 |
| $\beta_1$ | 0.0304 | 0.0002 | 154.1255 | 0.5930 | 0.0011 | 541.5522 | 0.0068 | 0.0000 | 1514.1876 |
| $\mu$ | 0.0000 | 0.0000 | -3.8761 | 0.0000 | 0.0000 | 17.4732 | 0.0000 | 0.0000 | -26.3314 |
| $\beta_2$ | 0.0203 | 0.0009 | 22.2264 | -0.0341 | 0.0022 | -15.5080 | 0.0282 | 0.0007 | 41.6822 |
| MLE | 42765.9910 | | | 44542.3161 | | | 44929.8602 | | |
| $\omega$ | 0.0000 | 0.0000 | 12.4431 | 0.0000 | 0.0000 | 2.9596 | 0.0000 | 0.0000 | 1.0842 |
| $\alpha$ | 0.8198 | 0.0006 | 1360.9102 | 0.5762 | 0.0002 | 3560.6497 | 0.9887 | 0.0004 | 2353.4899 |
| $\beta_1$ | 0.0371 | 0.0000 | 1192.2971 | 0.1884 | 0.0008 | 227.4757 | 0.0000 | 0.0011 | 0.0001 |
| $\mu$ | 0.0000 | 0.0000 | -11.4484 | 0.0000 | 0.0000 | -7.5227 | 0.0000 | 0.0000 | 5.1507 |
| $\beta_2$ | 0.0089 | 0.0006 | 14.3738 | 0.0018 | 0.0005 | 4.0461 | -0.0027 | 0.0005 | -5.8967 |
| $\nu$ | 2.6373 | 0.0017 | 1512.0350 | 2.6446 | 0.0010 | 2749.2128 | 4.0483 | 0.0009 | 4313.8770 |
| MLE | 45369.1158 | | | 47564.2546 | | | 48101.5461 | | |
| Likelihood Ratio test | 5206.2496 | | | 6043.8770 | | | 6343.3718 | | |
| IGARCH | | | | | | | | | |
| $\omega$ | 0.0000 | 0.0000 | 0.2192 | 0.0000 | 0.0000 | 0.7497 | 0.0000 | 0.0000 | 0.0000 |
| $\beta_1$ | 0.7089 | 0.0004 | 1760.1020 | 0.6824 | 0.0002 | 3888.2914 | 0.8228 | 0.0003 | 2908.9444 |
| $\mu$ | 0.0000 | 0.0000 | 10.0915 | 0.0000 | 0.0000 | 35.8842 | 0.0001 | 0.0000 | 64.1499 |
| $\beta_2$ | -0.0304 | 0.0018 | -16.5784 | -0.0431 | 0.0010 | -45.2981 | -0.0919 | 0.0017 | -55.3531 |
| MLE | 42344.3967 | | | 44177.9391 | | | 43514.4357 | | |
| $\omega$ | 0.0000 | 0.0000 | 1.3885 | 0.0000 | 0.0000 | 0.6712 | 0.0000 | 0.0000 | 0.0121 |
| $\beta_1$ | 0.4383 | 0.0004 | 1185.3084 | 0.7203 | 0.0008 | 854.3994 | 0.7302 | 0.0004 | 1893.4146 |
| $\mu$ | 0.0000 | 0.0000 | -13.2122 | 0.0000 | 0.0000 | -5.9148 | 0.0000 | 0.0000 | -1.1216 |
| $\beta_2$ | 0.0077 | 0.0007 | 11.5348 | 0.0016 | 0.0006 | 2.6460 | -0.0016 | 0.0004 | -3.6037 |
| $\nu$ | 3.0641 | 0.0011 | 2844.4519 | 3.0481 | 0.0011 | 2500.5451 | 3.2676 | 0.0006 | 5333.4752 |
| MLE | 45030.8585 | | | 47176.7213 | | | 47812.6058 | | |
| Likelihood Ratio test | 5372.9236 | | | 5997.5644 | | | 8596.3402 | | |
| Likelihood Ratio test (GARCH and IGARCH) | 676.5146 | | | 775.0666 | | | 577.8806 | | |

Table B.6: The estimations of raw sugar net conveience yield with Gaussian and Standardised-t error distributions

| | 2nd Contract | | | 4th Contract | | | 6th Contract | | |
|---|---|---|---|---|---|---|---|---|---|
| GARCH | Coefficient | S.E. | t-Statistic | Coefficient | S.E. | t-Statistic | Coefficient | S.E. | t-Statistic |
| $\omega$ | 0.0000 | 0.0000 | 1.5446 | 0.0000 | 0.0000 | 6.6090 | 0.0000 | 0.0000 | 0.0008 |
| $\alpha$ | 0.4388 | 0.0013 | 339.9290 | 0.3165 | 0.0011 | 285.7781 | 0.2726 | 0.0002 | 1605.8872 |
| $\beta_1$ | 0.5393 | 0.0011 | 482.8717 | 0.6422 | 0.0012 | 521.0957 | 0.7174 | 0.0004 | 1629.4472 |
| $\mu$ | 0.0000 | 0.0000 | -2.1774 | 0.0000 | 0.0000 | 42.9026 | 0.0000 | 0.0000 | 37.8848 |
| $\beta_2$ | -0.0054 | 0.0011 | -5.0603 | -0.0355 | 0.0013 | -27.9752 | -0.0104 | 0.0005 | -21.1717 |
| MLE | 43245.3114 | | | 42865.4394 | | | 45818.9278 | | |
| $\omega$ | 0.0000 | 0.0000 | 1.9471 | 0.0000 | 0.0000 | 1.9706 | 0.0000 | 0.0000 | 0.0001 |
| $\alpha$ | 0.7181 | 0.0012 | 600.1748 | 0.8790 | 0.0025 | 358.1050 | 0.0025 | 0.0010 | 2.4449 |
| $\beta_1$ | 0.2359 | 0.0024 | 98.5995 | 0.0000 | 0.0000 | 0.0062 | 0.9975 | 0.0010 | 959.6556 |
| $\mu$ | 0.0000 | 0.0000 | -16.3771 | 0.0000 | 0.0000 | -11.7839 | 0.0000 | 0.0000 | 0.2529 |
| $\beta_2$ | 0.0046 | 0.0009 | 5.3581 | 0.0001 | 0.0000 | 92.9733 | -0.0029 | 0.0000 | -356.2177 |
| $\nu$ | 4.6803 | 0.0173 | 271.3211 | 2.4081 | 0.0016 | 1508.1931 | 2.6746 | 0.0008 | 3294.1225 |
| MLE | 44530.3605 | | | 45688.1705 | | | 47616.0348 | | |
| Likelihood Ratio test | 2570.0981 | | | 5645.4622 | | | 3594.2140 | | |
| IGARCH | | | | | | | | | |
| $\omega$ | 0.0000 | 0.0000 | 1.2900 | 0.0000 | 0.0000 | 9.3775 | 0.0000 | 0.0000 | 0.0003 |
| $\beta_1$ | 0.5330 | 0.0002 | 3181.6101 | 0.5820 | 0.0003 | 2137.8622 | 0.8140 | 0.0001 | 9107.1109 |
| $\mu$ | 0.0000 | 0.0000 | -2.8539 | 0.0000 | 0.0000 | 27.1057 | 0.0000 | 0.0000 | 19.0189 |
| $\beta_2$ | -0.0038 | 0.0011 | -3.5068 | -0.0301 | 0.0014 | -21.8510 | -0.0066 | 0.0009 | -7.3095 |
| MLE | 43207.1176 | | | 42639.1711 | | | 45784.2644 | | |
| $\omega$ | 0.0000 | 0.0000 | 0.5450 | 0.0000 | 0.0000 | 1.8957 | 0.0000 | 0.0000 | 0.0001 |
| $\beta_1$ | 0.4748 | 0.0007 | 722.2122 | 0.5490 | 0.0084 | 65.3644 | 0.9804 | 0.0015 | 659.3300 |
| $\mu$ | 0.0000 | 0.0000 | -11.8201 | 0.0000 | 0.0000 | -5.8608 | 0.0000 | 0.0000 | -0.4552 |
| $\beta_2$ | 0.0033 | 0.0009 | 3.6652 | -0.0004 | 0.0006 | -0.6936 | -0.0014 | 0.0005 | -2.9176 |
| $\nu$ | 3.5859 | 0.0024 | 1489.1039 | 2.7939 | 0.0102 | 274.8038 | 2.7387 | 0.0019 | 1443.3603 |
| MLE | 44518.3124 | | | 45674.8703 | | | 47571.4940 | | |
| Likelihood Ratio test | 2622.3896 | | | 6071.3985 | | | 3574.4592 | | |
| Likelihood Ratio test (GARCH and IGARCH) | 24.0962 | | | 26.6004 | | | 89.0816 | | |

Table B.7: The estimations of rubber net conveience yield and Thai Baht/Yen exchange rate

| | 2nd Contract | | | 4th Contract | | | 6th Contract | | |
|---|---|---|---|---|---|---|---|---|---|
| GARCH | Coefficient | S.E. | t-Statistic | Coefficient | S.E. | t-Statistic | Coefficient | S.E. | t-Statistic |
| $\omega$ | 0.0000 | 0.0000 | 38.7529 | 0.0000 | 0.0000 | 6.7526 | 0.0000 | 0.0000 | 0.5255 |
| $\alpha$ | 0.6540 | 0.0015 | 450.2843 | 0.2998 | 0.0034 | 88.2367 | 0.1305 | 0.0003 | 374.4027 |
| $\beta_1$ | 0.3457 | 0.0017 | 202.5910 | 0.6596 | 0.0015 | 427.8587 | 0.8695 | 0.0016 | 551.5772 |
| $\mu$ | 0.0000 | 0.0000 | -15.0170 | 0.0000 | 0.0000 | -9.3625 | 0.0000 | 0.0000 | -8.9295 |
| $\beta_2$ | -0.1535 | 0.0029 | -52.6697 | -0.0480 | 0.0019 | -24.6500 | -0.0424 | 0.0020 | -21.1747 |
| $\beta_3$ | -0.0012 | 0.0002 | -5.8538 | -0.0006 | 0.0001 | -4.3706 | -0.0002 | 0.0001 | -2.9738 |
| $\beta_4$ | -0.0001 | 0.0001 | -0.4077 | -0.0001 | 0.0000 | -2.5837 | 0.0000 | 0.0000 | 0.2455 |
| MLE | 21118.7307 | | | 23662.7418 | | | 24886.1007 | | |
| $\omega$ | 0.0000 | 0.0000 | 6.3303 | 0.0000 | 0.0000 | 59.0152 | 0.0000 | 0.0000 | 0.0016 |
| $\alpha$ | 0.4431 | 0.0037 | 119.2863 | 0.5649 | 0.0000 | 17789.9058 | 0.0613 | 0.0053 | 11.6273 |
| $\beta_1$ | 0.4469 | 0.0165 | 27.0659 | 0.1566 | 0.0001 | 2159.5610 | 0.9387 | 0.0046 | 204.6685 |
| $\mu$ | 0.0000 | 0.0000 | -9.7808 | 0.0000 | 0.0000 | -1.3446 | 0.0000 | 0.0000 | -0.7142 |
| $\beta_2$ | -0.0658 | 0.0042 | -15.8259 | -0.0044 | 0.0018 | -2.4549 | -0.0073 | 0.0030 | -2.4387 |
| $\beta_3$ | -0.0007 | 0.0002 | -3.4585 | -0.0002 | 0.0001 | -2.3912 | -0.0001 | 0.0001 | -1.4650 |
| $\beta_4$ | 0.0001 | 0.0001 | 0.9092 | 0.0000 | 0.0000 | 1.8206 | 0.0000 | 0.0000 | 1.7443 |
| $\nu$ | 3.4930 | 0.0004 | 8523.2590 | 3.0779 | 0.0000 | 863727.1863 | 3.4957 | 0.0449 | 77.8505 |
| MLE | 21563.0733 | | | 23990.1420 | | | 25255.5456 | | |
| Likelihood Ratio test | 888.6852 | | | 654.8004 | | | 738.8898 | | |
| IGARCH | | | | | | | | | |
| $\omega$ | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 11.0360 | 0.0000 | 0.0000 | 0.0000 |
| $\beta_1$ | 0.9348 | 0.0023 | 414.1753 | 0.5491 | 0.0028 | 195.2271 | 0.8883 | 0.0066 | 134.0911 |
| $\mu$ | 0.0000 | 0.0000 | -10.5736 | 0.0000 | 0.0000 | -10.7620 | 0.0000 | 0.0000 | -11.4706 |
| $\beta_2$ | -0.1891 | 0.0036 | -52.7274 | -0.0522 | 0.0021 | -25.2567 | -0.0480 | 0.0021 | -22.5702 |
| $\beta_3$ | -0.0029 | 0.0005 | -5.5068 | -0.0006 | 0.0001 | -5.0738 | -0.0004 | 0.0001 | -4.2039 |
| $\beta_4$ | 0.0000 | 0.0001 | 0.2922 | 0.0000 | 0.0000 | 1.4386 | 0.0000 | 0.0000 | 0.4421 |
| MLE | 20512.5798 | | | 23593.4531 | | | 24800.9444 | | |
| $\omega$ | 0.0000 | 0.0000 | 0.0111 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| $\beta_1$ | 0.9954 | 0.0034 | 293.9451 | 0.9303 | 0.0001 | 15669.5607 | 0.9279 | 0.0073 | 127.3522 |
| $\mu$ | 0.0000 | 0.0000 | -1.1350 | 0.0000 | 0.0000 | -2.5065 | 0.0000 | 0.0000 | -0.4445 |
| $\beta_2$ | -0.0183 | 0.0098 | -1.8757 | -0.0127 | 0.0022 | -5.7709 | -0.0073 | 0.0016 | -4.4508 |
| $\beta_3$ | -0.0008 | 0.0003 | -2.5117 | -0.0002 | 0.0001 | -1.4966 | -0.0002 | 0.0001 | -2.0798 |
| $\beta_4$ | -0.0004 | 0.0001 | -6.3845 | 0.0000 | 0.0000 | -0.1090 | 0.0000 | 0.0000 | 1.0054 |
| $\nu$ | 2.2650 | 0.1338 | 16.9330 | 3.3649 | 0.0159 | 211.3726 | 3.5204 | 0.0054 | 651.4128 |
| MLE | 21408.6676 | | | 23916.3032 | | | 25236.0998 | | |
| Likelihood Ratio test | 1792.1756 | | | 645.7002 | | | 870.3108 | | |
| Likelihood Ratio test (GARCH and IGARCH) | 308.8114 | | | 147.6776 | | | 38.8916 | | |

Table B.8: The estimations of white sugar net conveience yield and Thai Baht/USD exchange rate

| | 2nd Contract | | | 4th Contract | | | 6th Contract | | |
|---|---|---|---|---|---|---|---|---|---|
| GARCH | Coefficient | S.E. | t-Statistic | Coefficient | S.E. | t-Statistic | Coefficient | S.E. | t-Statistic |
| $\omega$ | 0.0000 | 0.0000 | 4.2837 | 0.0000 | 0.0000 | 0.0044 | 0.0000 | 0.0000 | 3.5029 |
| $\alpha$ | 0.8458 | 0.0006 | 1502.7361 | 0.8419 | 0.0004 | 2130.1954 | 0.7945 | 0.0032 | 248.0171 |
| $\beta_1$ | 0.1526 | 0.0016 | 94.0759 | 0.1486 | 0.0311 | 4.7733 | 0.0761 | 0.0039 | 19.5545 |
| $\mu$ | 0.0000 | 0.0000 | -1.1563 | 0.0000 | 0.0000 | 0.6943 | 0.0001 | 0.0000 | 26.9606 |
| $\beta_2$ | -0.0127 | 0.0013 | -9.7357 | -0.0256 | 0.0226 | -1.1333 | -0.0841 | 0.0034 | -24.9666 |
| $\beta_3$ | 0.0003 | 0.0001 | 3.1375 | 0.0005 | 0.0016 | 0.2960 | -0.0033 | 0.0005 | -7.1400 |
| $\beta_4$ | 0.0001 | 0.0000 | 2.3341 | 0.0000 | 0.0015 | 0.0260 | -0.0009 | 0.0001 | -7.6895 |
| MLE | 26927.3590 | | | 28075.7755 | | | 27945.4282 | | |
| $\omega$ | 0.0000 | 0.0000 | 5.5053 | 0.0000 | 0.0000 | 2.9905 | 0.0000 | 0.0000 | 69.1872 |
| $\alpha$ | 0.6910 | 0.0021 | 325.4935 | 0.8419 | 0.0001 | 13353.6972 | 0.9826 | 0.0001 | 13850.8357 |
| $\beta_1$ | 0.1227 | 0.0000 | 83334.3219 | 0.1260 | 0.0001 | 1879.4279 | 0.0152 | 0.0001 | 119.6175 |
| $\mu$ | 0.0000 | 0.0000 | -7.3357 | 0.0000 | 0.0000 | -7.0742 | 0.0000 | 0.0000 | -0.7852 |
| $\beta_2$ | 0.0100 | 0.0013 | 7.9043 | 0.0065 | 0.0010 | 6.7750 | -0.0011 | 0.0012 | -0.8710 |
| $\beta_3$ | -0.0001 | 0.0000 | -2.8071 | 0.0000 | 0.0000 | -0.3169 | 0.0000 | 0.0000 | 0.6780 |
| $\beta_4$ | 0.0000 | 0.0000 | 1.5660 | 0.0001 | 0.0000 | 3.1743 | 0.0001 | 0.0000 | 3.3951 |
| $\nu$ | 2.7796 | 0.0016 | 1788.0625 | 2.7774 | 0.0000 | 12946.3661 | 2.0088 | 0.0005 | 3682.7066 |
| MLE | 28120.7748 | | | 29603.3454 | | | 30211.5477 | | |
| Likelihood Ratio test | 2386.8316 | | | 3055.1398 | | | 4532.2390 | | |
| IGARCH | | | | | | | | | |
| $\omega$ | 0.0000 | 0.0000 | 1.3574 | 0.0000 | 0.0000 | 0.2721 | 0.0000 | 0.0000 | 0.0421 |
| $\beta_1$ | 0.2309 | 0.0006 | 375.8053 | 0.1796 | 0.0012 | 150.6757 | 0.0360 | 0.0004 | 81.0467 |
| $\mu$ | 0.0000 | 0.0000 | 0.8017 | 0.0000 | 0.0000 | 0.3278 | -0.0002 | 0.0000 | -145.9560 |
| $\beta_2$ | -0.0114 | 0.0016 | -7.2955 | -0.0126 | 0.0002 | -78.0002 | 0.2439 | 0.0001 | 1857.4852 |
| $\beta_3$ | 0.0005 | 0.0001 | 5.5468 | 0.0000 | 0.0021 | 0.0000 | 0.0004 | 0.0005 | 0.8677 |
| $\beta_4$ | 0.0000 | 0.0001 | -0.6321 | 0.0001 | 0.0007 | 0.0718 | 0.0005 | 0.0002 | 2.8708 |
| MLE | 26904.8409 | | | 28050.4030 | | | 27786.0733 | | |
| $\omega$ | 0.0000 | 0.0000 | 1.3065 | 0.0000 | 0.0000 | 0.8067 | 0.0000 | 0.0000 | 0.4571 |
| $\beta_1$ | 0.4085 | 0.0057 | 72.1934 | 0.3369 | 0.0015 | 220.1412 | 0.0124 | 0.0012 | 10.5898 |
| $\mu$ | 0.0000 | 0.0000 | -10.6588 | 0.0000 | 0.0000 | -8.1489 | 0.0000 | 0.0000 | 4.5225 |
| $\beta_2$ | 0.0132 | 0.0013 | 10.4823 | 0.0043 | 0.0008 | 5.4211 | -0.0104 | 0.0023 | -4.5851 |
| $\beta_3$ | 0.0000 | 0.0000 | -0.6529 | 0.0000 | 0.0000 | -0.1009 | -0.0002 | 0.0000 | -4.8265 |
| $\beta_4$ | 0.0000 | 0.0000 | 1.1865 | 0.0001 | 0.0000 | 3.6356 | -0.0001 | 0.0001 | -1.0635 |
| $\nu$ | 3.1916 | 0.0118 | 270.7760 | 2.9974 | 0.0018 | 1620.7267 | 3.2650 | 0.0000 | 9279.0635 |
| MLE | 27999.6122 | | | 29417.5857 | | | 29960.8673 | | |
| Likelihood Ratio test | 2189.5426 | | | 2734.3654 | | | 4349.5880 | | |
| Likelihood Ratio test (GARCH and IGARCH) | 242.3252 | | | 371.5194 | | | 501.3608 | | |

Table B.9: The estimations of white sugar net conveience yield and Brazil Real/USD exchange rate

| | 2nd Contract | | | 4th Contract | | | 6th Contract | | |
|---|---|---|---|---|---|---|---|---|---|
| GARCH | Coefficient | S.E. | t-Statistic | Coefficient | S.E. | t-Statistic | Coefficient | S.E. | t-Statistic |
| $\omega$ | 0.0000 | 0.0000 | 4.7213 | 0.0000 | 0.0000 | 8.4947 | 0.0000 | 0.0000 | 1.1218 |
| $\alpha$ | 0.4704 | 0.0022 | 215.1577 | 0.6001 | 0.0005 | 1295.1041 | 0.0998 | 0.0006 | 181.5033 |
| $\beta_1$ | 0.0755 | 0.0008 | 95.9917 | 0.0978 | 0.0007 | 145.8671 | 0.6592 | 0.0011 | 591.9781 |
| $\mu$ | 0.0000 | 0.0000 | 18.4155 | 0.0000 | 0.0000 | 0.7289 | 0.0000 | 0.0000 | -0.4259 |
| $\beta_2$ | -0.1065 | 0.0019 | -56.7838 | -0.0040 | 0.0000 | -177.6149 | 0.0022 | 0.0001 | 20.4911 |
| $\beta_3$ | 0.0000 | 0.0000 | -0.0737 | 0.0008 | 0.0000 | 26.9098 | 0.0000 | 0.0001 | -0.1144 |
| $\beta_4$ | 0.0000 | 0.0001 | -0.2335 | 0.0000 | 0.0000 | -0.2005 | 0.0004 | 0.0001 | 6.2967 |
| MLE | 26351.2899 | | | 27740.2753 | | | 28475.4947 | | |
| $\omega$ | 0.0000 | 0.0000 | 5.3444 | 0.0000 | 0.0000 | 4.3678 | 0.0000 | 0.0000 | 0.0148 |
| $\alpha$ | 0.7999 | 0.0041 | 196.9467 | 0.8547 | 0.0000 | 217230.9335 | 0.1005 | 0.0076 | 13.1701 |
| $\beta_1$ | 0.1041 | 0.0000 | 9247.7965 | 0.1452 | 0.0000 | 40350.6101 | 0.6629 | 0.0041 | 160.2355 |
| $\mu$ | 0.0000 | 0.0000 | -9.7220 | 0.0000 | 0.0000 | -5.9147 | 0.0000 | 0.0014 | 0.0000 |
| $\beta_2$ | 0.0103 | 0.0011 | 9.4657 | 0.0039 | 0.0008 | 4.8352 | 0.0060 | 0.0000 | 2208.6638 |
| $\beta_3$ | 0.0000 | 0.0000 | -0.5835 | 0.0000 | 0.0000 | -2.1073 | -0.0004 | 0.0000 | -22.4839 |
| $\beta_4$ | 0.0001 | 0.0000 | 1.7431 | 0.0001 | 0.0000 | 4.5816 | 0.0001 | 0.0000 | 10.0608 |
| $\nu$ | 2.8785 | 0.0046 | 619.7329 | 2.7313 | 0.0000 | 362141.8869 | 3.5926 | 0.0033 | 1082.9853 |
| MLE | 28133.4210 | | | 29613.1211 | | | 29795.9923 | | |
| Likelihood Ratio test | 3564.2622 | | | 3745.6916 | | | 2640.9952 | | |
| IGARCH | | | | | | | | | |
| $\omega$ | 0.0000 | 0.0000 | 0.0601 | 0.0000 | 0.0000 | 0.9747 | 0.0000 | 0.0000 | 3.4942 |
| $\beta_1$ | 0.0616 | 0.0003 | 243.4471 | 0.1032 | 0.0005 | 192.7702 | 0.6378 | 0.0020 | 313.0692 |
| $\mu$ | 0.0000 | 0.0000 | 15.6061 | 0.0000 | 0.0000 | -1.2621 | 0.0000 | 0.0000 | 76.2945 |
| $\beta_2$ | -0.0999 | 0.0015 | -66.4669 | -0.0030 | 0.0017 | -1.7174 | -0.0457 | 0.0049 | -9.3591 |
| $\beta_3$ | -0.0002 | 0.0000 | -5.1274 | 0.0006 | 0.0000 | 17.4437 | 0.0003 | 0.0000 | 12.3347 |
| $\beta_4$ | -0.0001 | 0.0000 | -3.3680 | 0.0000 | 0.0000 | 1.7112 | -0.0001 | 0.0000 | -3.2452 |
| MLE | 26246.2938 | | | 27658.7857 | | | 28454.3927 | | |
| $\omega$ | 0.0000 | 0.0000 | 0.5949 | 0.0000 | 0.0000 | 0.0498 | 0.0000 | 0.0000 | 1.4145 |
| $\beta_1$ | 0.0804 | 0.0020 | 41.1458 | 0.1032 | 0.0022 | 46.6666 | 0.4580 | 0.0034 | 134.6789 |
| $\mu$ | 0.0000 | 0.0000 | -8.6819 | 0.0000 | 0.0000 | -1.1442 | 0.0000 | 0.0000 | 13.1843 |
| $\beta_2$ | 0.0070 | 0.0011 | 6.2093 | 0.0011 | 0.0000 | 65.7082 | -0.0502 | 0.0031 | -16.4164 |
| $\beta_3$ | 0.0000 | 0.0000 | -1.3730 | -0.0001 | 0.0002 | -0.4428 | 0.0004 | 0.0001 | 7.0216 |
| $\beta_4$ | 0.0001 | 0.0000 | 2.1097 | 0.0002 | 0.0001 | 1.8756 | 0.0000 | 0.0003 | -0.0078 |
| $\nu$ | 3.9678 | 0.0001 | 32084.2052 | 2.9999 | 0.0528 | 56.7990 | 3.8162 | 0.0170 | 224.0456 |
| MLE | 27765.6412 | | | 29599.0401 | | | 29708.8579 | | |
| Likelihood Ratio test | 3038.6948 | | | 3880.5088 | | | 2508.9304 | | |
| Likelihood Ratio test (GARCH and IGARCH) | 735.5596 | | | 28.1620 | | | 174.2688 | | |

Table B.10: The estimations of white sugar net conveience yield and Euro/USD exchange rate

| | 2nd Contract | | | 4th Contract | | | 6th Contract | | |
|---|---|---|---|---|---|---|---|---|---|
| GARCH | Coefficient | S.E. | t-Statistic | Coefficient | S.E. | t-Statistic | Coefficient | S.E. | t-Statistic |
| $\omega$ | 0.0000 | 0.0000 | 2.5432 | 0.0000 | 0.0000 | 0.3683 | 0.0000 | 0.0000 | 1.0285 |
| $\alpha$ | 0.7158 | 0.0001 | 9012.6429 | 0.5687 | 0.0065 | 87.9300 | 0.6316 | 0.0029 | 215.0267 |
| $\beta_1$ | 0.0365 | 0.0000 | 746.5196 | 0.0636 | 0.0020 | 32.0057 | 0.0097 | 0.0044 | 2.1857 |
| $\mu$ | 0.0000 | 0.0000 | 2.7548 | 0.0000 | 0.0000 | 4.9817 | 0.0000 | 0.0000 | 16.4200 |
| $\beta_2$ | -0.0072 | 0.0020 | -3.6480 | 0.0028 | 0.0012 | 2.2956 | -0.0193 | 0.0013 | -15.4576 |
| $\beta_3$ | -0.0004 | 0.0001 | -4.8640 | -0.0004 | 0.0001 | -7.9419 | -0.0001 | 0.0001 | -0.5434 |
| $\beta_4$ | 0.0001 | 0.0000 | 1.7887 | 0.0001 | 0.0000 | 3.1829 | -0.0002 | 0.0000 | -3.8502 |
| MLE | 22937.2114 | | | 24499.6965 | | | 24767.5073 | | |
| $\omega$ | 0.0000 | 0.0000 | 2.7302 | 0.0000 | 0.0000 | 0.7379 | 0.0000 | 0.0000 | 1.5524 |
| $\alpha$ | 0.7112 | 0.0023 | 312.6087 | 0.8046 | 0.0019 | 428.2330 | 0.9711 | 0.0009 | 1112.9279 |
| $\beta_1$ | 0.2799 | 0.0021 | 135.0744 | 0.0045 | 0.0000 | 228.7406 | 0.0289 | 0.0009 | 33.0945 |
| $\mu$ | 0.0000 | 0.0000 | -5.2836 | 0.0000 | 0.0000 | -4.5864 | 0.0000 | 0.0000 | -0.2404 |
| $\beta_2$ | 0.0070 | 0.0010 | 6.7304 | 0.0034 | 0.0008 | 4.3779 | -0.0016 | 0.0007 | -2.2497 |
| $\beta_3$ | -0.0001 | 0.0000 | -1.4721 | -0.0001 | 0.0000 | -4.5603 | -0.0002 | 0.0000 | -6.3852 |
| $\beta_4$ | 0.0000 | 0.0000 | 1.8504 | 0.0001 | 0.0000 | 6.8853 | 0.0001 | 0.0000 | 4.8091 |
| $\nu$ | 2.4157 | 0.0067 | 361.6836 | 3.4512 | 0.0186 | 185.1091 | 2.8680 | 0.0062 | 462.8768 |
| MLE | 23770.7553 | | | 25042.0582 | | | 25681.6744 | | |
| Likelihood Ratio test | 1667.0878 | | | 1084.7234 | | | 1828.3342 | | |
| IGARCH | | | | | | | | | |
| $\omega$ | 0.0000 | 0.0000 | 1.2798 | 0.0000 | 0.0000 | 0.2326 | 0.0000 | 0.0000 | 0.7022 |
| $\beta_1$ | 0.0228 | 0.0006 | 38.6536 | 0.0163 | 0.0010 | 16.6403 | 0.0208 | 0.0008 | 25.4102 |
| $\mu$ | 0.0000 | 0.0000 | 1.0597 | 0.0000 | 0.0000 | 7.5072 | 0.0000 | 0.0000 | 8.5869 |
| $\beta_2$ | -0.0039 | 0.0015 | -2.6597 | 0.0013 | 0.0007 | 1.9043 | -0.0132 | 0.0007 | -18.6661 |
| $\beta_3$ | -0.0003 | 0.0001 | -4.5360 | -0.0003 | 0.0000 | -6.0009 | -0.0001 | 0.0000 | -1.3126 |
| $\beta_4$ | 0.0000 | 0.0000 | 1.0096 | 0.0001 | 0.0000 | 1.5355 | 0.0000 | 0.0000 | -1.3760 |
| MLE | 22772.3981 | | | 23926.8286 | | | 24212.1192 | | |
| $\omega$ | 0.0000 | 0.0000 | 6.9826 | 0.0000 | 0.0000 | 0.9961 | 0.0000 | 0.0000 | 0.6729 |
| $\beta_1$ | 0.0673 | 0.0035 | 19.1275 | 0.0906 | 0.0050 | 17.9907 | 0.0725 | 0.0029 | 24.9941 |
| $\mu$ | 0.0000 | 0.0000 | -6.3631 | 0.0000 | 0.0000 | -5.2936 | 0.0000 | 0.0000 | -4.3298 |
| $\beta_2$ | 0.0085 | 0.0011 | 7.7645 | 0.0041 | 0.0007 | 5.5389 | 0.0069 | 0.0014 | 4.8678 |
| $\beta_3$ | -0.0001 | 0.0001 | -2.5374 | -0.0002 | 0.0000 | -4.4697 | -0.0001 | 0.0001 | -2.8558 |
| $\beta_4$ | 0.0001 | 0.0000 | 3.2529 | 0.0000 | 0.0000 | 1.6699 | 0.0001 | 0.0000 | 4.5117 |
| $\nu$ | 2.6078 | 0.0038 | 691.4605 | 2.8397 | 0.0268 | 105.7816 | 3.9472 | 0.0243 | 162.6906 |
| MLE | 23741.3007 | | | 25002.0434 | | | 25662.2866 | | |
| Likelihood Ratio test | 1937.8052 | | | 2150.4296 | | | 2900.3348 | | |
| Likelihood Ratio test (GARCH and IGARCH) | 58.9092 | | | 80.0296 | | | 38.7756 | | |

Table B.11: The estimations of raw sugar net conveience yield and Thai Baht/USD exchange rate

| | 2nd Contract | | | 4th Contract | | | 6th Contract | | |
|---|---|---|---|---|---|---|---|---|---|
| GARCH | Coefficient | S.E. | t-Statistic | Coefficient | S.E. | t-Statistic | Coefficient | S.E. | t-Statistic |
| $\omega$ | 0.0000 | 0.0000 | 0.1727 | 0.0000 | 0.0000 | 17.2123 | 0.0000 | 0.0000 | 0.0000 |
| $\alpha$ | 0.3278 | 0.0068 | 48.0781 | 0.9320 | 0.0064 | 145.0369 | 0.0336 | 0.0001 | 251.9164 |
| $\beta_1$ | 0.6719 | 0.0021 | 322.7934 | 0.0679 | 0.0022 | 30.9037 | 0.9663 | 0.0249 | 38.7315 |
| $\mu$ | 0.0000 | 0.0000 | -14.7027 | 0.0000 | 0.0000 | 10.1615 | 0.0000 | 0.0000 | 14.7172 |
| $\beta_2$ | 0.0024 | 0.0007 | 3.4957 | -0.0010 | 0.0016 | -0.6149 | -0.0083 | 0.0008 | -10.4237 |
| $\beta_3$ | -0.0002 | 0.0001 | -4.3049 | -0.0020 | 0.0002 | -12.1446 | -0.0001 | 0.0001 | -1.6181 |
| $\beta_4$ | -0.0002 | 0.0000 | -9.3364 | 0.0010 | 0.0001 | 7.0567 | 0.0003 | 0.0000 | 11.4619 |
| MLE | 26728.0717 | | | 27131.5977 | | | 28412.8355 | | |
| $\omega$ | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 1.9959 | 0.0000 | 0.0000 | 0.0779 |
| $\alpha$ | 0.3698 | 0.0022 | 167.8433 | 0.3381 | 0.0036 | 92.9474 | 0.0030 | 0.0000 | 70.0821 |
| $\beta_1$ | 0.6302 | 0.0022 | 286.2424 | 0.4279 | 0.0055 | 78.3275 | 0.9939 | 0.0057 | 175.3835 |
| $\mu$ | 0.0000 | 0.0000 | -12.1081 | 0.0000 | 0.0000 | -4.4358 | 0.0000 | 0.0000 | 0.6948 |
| $\beta_2$ | 0.0044 | 0.0011 | 3.9999 | -0.0009 | 0.0009 | -1.0234 | -0.0036 | 0.0006 | -5.9836 |
| $\beta_3$ | 0.0000 | 0.0001 | -0.2968 | 0.0000 | 0.0001 | 0.4528 | 0.0000 | 0.0000 | -0.3935 |
| $\beta_4$ | 0.0001 | 0.0000 | 5.0160 | 0.0002 | 0.0000 | 6.3089 | 0.0002 | 0.0000 | 7.1628 |
| $\nu$ | 4.5267 | 0.0061 | 738.3213 | 2.5780 | 0.0031 | 824.4197 | 2.2524 | 0.0036 | 630.2720 |
| MLE | 27275.9436 | | | 28092.5950 | | | 29576.3324 | | |
| Likelihood Ratio test | 1095.7438 | | | 1921.9946 | | | 2326.9938 | | |
| IGARCH | | | | | | | | | |
| $\omega$ | 0.0000 | 0.0000 | 0.3148 | 0.0000 | 0.0000 | 7.2709 | 0.0000 | 0.0000 | 0.0001 |
| $\beta_1$ | 0.5833 | 0.0001 | 9981.8211 | 0.1185 | 0.0017 | 68.8607 | 0.9664 | 0.0036 | 266.6109 |
| $\mu$ | 0.0000 | 0.0000 | -11.5884 | 0.0000 | 0.0000 | 19.2023 | 0.0000 | 0.0000 | 13.2225 |
| $\beta_2$ | 0.0145 | 0.0029 | 4.9514 | -0.0153 | 0.0014 | -10.6115 | -0.0083 | 0.0009 | -9.5181 |
| $\beta_3$ | -0.0002 | 0.0001 | -2.8302 | -0.0005 | 0.0001 | -4.1795 | -0.0001 | 0.0001 | -1.4858 |
| $\beta_4$ | -0.0003 | 0.0000 | -7.6135 | 0.0012 | 0.0001 | 19.4571 | 0.0003 | 0.0000 | 10.9934 |
| MLE | 26639.3850 | | | 27113.1749 | | | 28410.0588 | | |
| $\omega$ | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 1.4802 | 0.0000 | 0.0000 | 0.0000 |
| $\beta_1$ | 0.6272 | 0.0057 | 109.9710 | 0.5649 | 0.0088 | 64.5166 | 0.9480 | 0.0031 | 303.1930 |
| $\mu$ | 0.0000 | 0.0000 | -12.1615 | 0.0000 | 0.0000 | -4.2654 | 0.0000 | 0.0000 | 3.5259 |
| $\beta_2$ | 0.0044 | 0.0010 | 4.2210 | -0.0008 | 0.0010 | -0.8618 | -0.0044 | 0.0001 | -33.4281 |
| $\beta_3$ | 0.0000 | 0.0001 | -0.5267 | 0.0000 | 0.0001 | 0.2882 | 0.0000 | 0.0000 | -0.3980 |
| $\beta_4$ | 0.0001 | 0.0000 | 4.9206 | 0.0002 | 0.0000 | 6.8076 | 0.0002 | 0.0000 | 8.7064 |
| $\nu$ | 4.5214 | 0.0103 | 437.5149 | 3.0311 | 0.0138 | 219.2960 | 2.9800 | 0.0031 | 967.3467 |
| MLE | 27259.9392 | | | 28048.2365 | | | 29393.2378 | | |
| Likelihood Ratio test | 1241.1084 | | | 1870.1232 | | | 1966.3580 | | |
| Likelihood Ratio test (GARCH and IGARCH) | 32.0088 | | | 88.7170 | | | 366.1892 | | |

Table B.12: The estimations of raw sugar net conveience yield and Brazil Real/USD exchange rate

| | 2nd Contract | | | 4th Contract | | | 6th Contract | | |
|---|---|---|---|---|---|---|---|---|---|
| GARCH | Coefficient | S.E. | t-Statistic | Coefficient | S.E. | t-Statistic | Coefficient | S.E. | t-Statistic |
| $\omega$ | 0.0000 | 0.0000 | 0.5126 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| $\alpha$ | 0.4634 | 0.0006 | 749.3771 | 0.0042 | 0.0007 | 5.9145 | 0.0343 | 0.0022 | 15.3051 |
| $\beta_1$ | 0.5332 | 0.0032 | 167.5191 | 0.9957 | 0.0004 | 2683.9772 | 0.9657 | 0.0256 | 37.7786 |
| $\mu$ | 0.0000 | 0.0000 | -10.6037 | 0.0000 | 0.0000 | -1.1959 | 0.0000 | 0.0000 | 11.8212 |
| $\beta_2$ | 0.0063 | 0.0021 | 2.9795 | -0.0241 | 0.0004 | -62.0443 | -0.0081 | 0.0009 | -9.4683 |
| $\beta_3$ | -0.0001 | 0.0000 | -1.3785 | -0.0017 | 0.0006 | -2.7489 | -0.0002 | 0.0000 | -6.6643 |
| $\beta_4$ | -0.0003 | 0.0000 | -8.9772 | 0.0003 | 0.0002 | 1.1963 | 0.0003 | 0.0000 | 11.7616 |
| MLE | 26736.8705 | | | 24272.7971 | | | 28414.5728 | | |
| $\omega$ | 0.0000 | 0.0000 | 4.5216 | 0.0000 | 0.0000 | 1.3000 | 0.0000 | 0.0000 | 0.0000 |
| $\alpha$ | 0.5291 | 0.0090 | 58.5218 | 0.0057 | 0.0003 | 17.1699 | 0.0531 | 0.0010 | 53.2832 |
| $\beta_1$ | 0.3861 | 0.0009 | 418.0847 | 0.9175 | 0.0035 | 263.5886 | 0.9440 | 0.0043 | 221.5836 |
| $\mu$ | 0.0000 | 0.0000 | -11.3893 | 0.0000 | 0.0000 | -16.1382 | 0.0000 | 0.0000 | 1.2780 |
| $\beta_2$ | 0.0038 | 0.0009 | 4.0820 | 0.0089 | 0.0001 | 145.0767 | -0.0041 | 0.0006 | -6.6444 |
| $\beta_3$ | -0.0009 | 0.0005 | -1.9142 | -0.0002 | 0.0001 | -2.5069 | 0.0000 | 0.0001 | -0.0405 |
| $\beta_4$ | 0.0001 | 0.0000 | 4.2196 | 0.0005 | 0.0000 | 19.3468 | 0.0002 | 0.0000 | 8.0777 |
| $\nu$ | 3.1367 | 0.0030 | 1040.3883 | 2.5195 | 0.0226 | 111.5496 | 3.2194 | 0.0054 | 593.9014 |
| MLE | 27588.5351 | | | 27805.1426 | | | 29395.6303 | | |
| Likelihood Ratio test | 1703.3292 | | | 7064.6910 | | | 1962.1150 | | |
| IGARCH | | | | | | | | | |
| $\omega$ | 0.0000 | 0.0000 | 0.2793 | 0.0000 | 0.0000 | 0.0001 | 0.0000 | 0.0000 | 0.0001 |
| $\beta_1$ | 0.6137 | 0.0076 | 80.9326 | 0.8193 | 0.0034 | 241.8960 | 0.9735 | 0.0085 | 114.1183 |
| $\mu$ | 0.0000 | 0.0000 | -15.3741 | 0.0001 | 0.0000 | 92.1200 | 0.0000 | 0.0000 | 7.3504 |
| $\beta_2$ | 0.0146 | 0.0010 | 14.0647 | -0.0138 | 0.0018 | -7.8623 | -0.0034 | 0.0007 | -4.7305 |
| $\beta_3$ | -0.0001 | 0.0000 | -3.6533 | -0.0002 | 0.0001 | -2.1375 | -0.0003 | 0.0000 | -10.2702 |
| $\beta_4$ | -0.0003 | 0.0000 | -10.3916 | -0.0012 | 0.0001 | -19.4205 | 0.0004 | 0.0000 | 12.7578 |
| MLE | 26532.1581 | | | 24127.9507 | | | 28395.7407 | | |
| $\omega$ | 0.0000 | 0.0000 | 17.1450 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0314 |
| $\beta_1$ | 0.3232 | 0.0010 | 322.1652 | 0.7626 | 0.0091 | 83.5400 | 0.6892 | 0.0259 | 26.5620 |
| $\mu$ | 0.0000 | 0.0000 | -9.2534 | 0.0000 | 0.0000 | -4.3710 | 0.0000 | 0.0000 | -8.8390 |
| $\beta_2$ | 0.0040 | 0.0009 | 4.3487 | -0.0019 | 0.0011 | -1.6818 | 0.0495 | 0.0004 | 113.6877 |
| $\beta_3$ | -0.0001 | 0.0000 | -1.6960 | -0.0012 | 0.0005 | -2.4330 | -0.0001 | 0.0001 | -1.2811 |
| $\beta_4$ | 0.0001 | 0.0000 | 5.3239 | 0.0001 | 0.0000 | 4.3902 | -0.0001 | 0.0000 | -3.1739 |
| $\nu$ | 2.0488 | 0.0015 | 1334.3976 | 3.3859 | 0.0136 | 248.8306 | 5.5822 | 0.0069 | 812.2068 |
| MLE | 27445.1225 | | | 27665.3131 | | | 28956.8566 | | |
| Likelihood Ratio test | 1825.9288 | | | 7074.7248 | | | 1122.2318 | | |
| Likelihood Ratio test (GARCH and IGARCH) | 286.8252 | | | 279.6590 | | | 877.5474 | | |

Table B.13: The estimations of raw sugar net conveience yield and Euro/USD exchange rate

| | 2nd Contract | | | 4th Contract | | | 6th Contract | | |
|---|---|---|---|---|---|---|---|---|---|
| GARCH | Coefficient | S.E. | t-Statistic | Coefficient | S.E. | t-Statistic | Coefficient | S.E. | t-Statistic |
| $\omega$ | 0.0000 | 0.0000 | 2.5185 | 0.0000 | 0.0000 | 1.7001 | 0.0000 | 0.0000 | 0.1653 |
| $\alpha$ | 0.9595 | 0.0049 | 195.1337 | 0.4928 | 0.0127 | 38.8004 | 0.6336 | 0.0059 | 106.8182 |
| $\beta_1$ | 0.0405 | 0.0002 | 217.3307 | 0.0750 | 0.0087 | 8.6294 | 0.0102 | 0.0026 | 3.9605 |
| $\mu$ | 0.0000 | 0.0000 | -33.6743 | 0.0000 | 0.0000 | 13.4346 | 0.0000 | 0.0000 | 3.5316 |
| $\beta_2$ | 0.0227 | 0.0009 | 24.6623 | 0.0016 | 0.0014 | 1.1566 | -0.0020 | 0.0009 | -2.2010 |
| $\beta_3$ | -0.0004 | 0.0000 | -10.1509 | 0.0008 | 0.0001 | 6.2339 | -0.0007 | 0.0000 | -21.8391 |
| $\beta_4$ | -0.0006 | 0.0000 | -14.1412 | 0.0011 | 0.0001 | 14.9292 | 0.0000 | 0.0001 | 0.5003 |
| MLE | 22861.3024 | | | 21749.0558 | | | 24092.3994 | | |
| $\omega$ | 0.0000 | 0.0000 | 0.0004 | 0.0000 | 0.0000 | 0.7410 | 0.0000 | 0.0000 | 2.5652 |
| $\alpha$ | 0.3582 | 0.0035 | 101.3033 | 0.3763 | 0.0028 | 133.8145 | 0.5081 | 0.0020 | 258.6439 |
| $\beta_1$ | 0.6418 | 0.0035 | 183.5247 | 0.5228 | 0.0026 | 201.2718 | 0.2567 | 0.0023 | 109.7199 |
| $\mu$ | 0.0000 | 0.0000 | -10.8413 | 0.0000 | 0.0000 | -6.0808 | 0.0000 | 0.0000 | -0.8975 |
| $\beta_2$ | 0.0046 | 0.0012 | 3.8012 | -0.0004 | 0.0008 | -0.5462 | -0.0023 | 0.0007 | -3.1247 |
| $\beta_3$ | -0.0002 | 0.0001 | -3.1820 | -0.0002 | 0.0000 | -3.4812 | -0.0001 | 0.0000 | -1.4484 |
| $\beta_4$ | 0.0001 | 0.0000 | 4.2076 | 0.0002 | 0.0000 | 7.4853 | 0.0002 | 0.0000 | 11.9864 |
| $\nu$ | 4.5523 | 0.0454 | 100.2657 | 3.4344 | 0.0029 | 1186.8486 | 2.7009 | 0.0087 | 310.4484 |
| MLE | 23135.6689 | | | 23654.4120 | | | 24979.6371 | | |
| Likelihood Ratio test | 548.7330 | | | 3810.7124 | | | 1774.4754 | | |
| IGARCH | | | | | | | | | |
| $\omega$ | 0.0000 | 0.0000 | 11.3375 | 0.0000 | 0.0000 | 3.3660 | 0.0000 | 0.0000 | 0.8437 |
| $\beta_1$ | 0.0349 | 0.0004 | 95.2924 | 0.0496 | 0.0014 | 35.1208 | 0.5292 | 0.0053 | 99.5767 |
| $\mu$ | 0.0000 | 0.0000 | -25.2442 | 0.0000 | 0.0000 | -1.0110 | -0.0005 | 0.0000 | -466.3038 |
| $\beta_2$ | 0.0221 | 0.0010 | 21.5428 | 0.0223 | 0.0026 | 8.7309 | 0.6590 | 0.0036 | 181.9424 |
| $\beta_3$ | -0.0004 | 0.0000 | -8.0001 | -0.0015 | 0.0001 | -16.4168 | 0.0007 | 0.0001 | 5.7257 |
| $\beta_4$ | -0.0006 | 0.0000 | -13.6504 | 0.0000 | 0.0001 | -0.5428 | -0.0009 | 0.0001 | -10.4166 |
| MLE | 22644.5887 | | | 21250.7051 | | | 23839.7613 | | |
| $\omega$ | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 14.6431 |
| $\beta_1$ | 0.6408 | 0.0038 | 168.4351 | 0.7626 | 0.0026 | 291.7149 | 0.5374 | 0.0057 | 93.9211 |
| $\mu$ | 0.0000 | 0.0000 | -12.3373 | 0.0000 | 0.0000 | -5.2253 | 0.0000 | 0.0000 | 0.2379 |
| $\beta_2$ | 0.0047 | 0.0012 | 3.9895 | -0.0012 | 0.0010 | -1.2194 | -0.0033 | 0.0006 | -5.9077 |
| $\beta_3$ | -0.0002 | 0.0000 | -3.7102 | -0.0001 | 0.0000 | -3.3909 | -0.0002 | 0.0000 | -4.9277 |
| $\beta_4$ | 0.0001 | 0.0000 | 4.1301 | 0.0001 | 0.0000 | 4.4152 | 0.0002 | 0.0000 | 8.8891 |
| $\nu$ | 4.5249 | 0.0067 | 672.5516 | 3.4270 | 0.0142 | 241.3682 | 2.0255 | 0.0060 | 337.6897 |
| MLE | 23131.1613 | | | 23497.6423 | | | 24505.7740 | | |
| Likelihood Ratio test | 973.1452 | | | 4493.8744 | | | 1332.0254 | | |
| Likelihood Ratio test (GARCH and IGARCH) | 9.0152 | | | 313.5394 | | | 947.7262 | | |

# Appendix C

# Rainfall Modelling and Insurance Pricing with Hybrid Distribution

Figure C.1: The monthly moving average and yearly moving moving average rainfall level of all weather stations

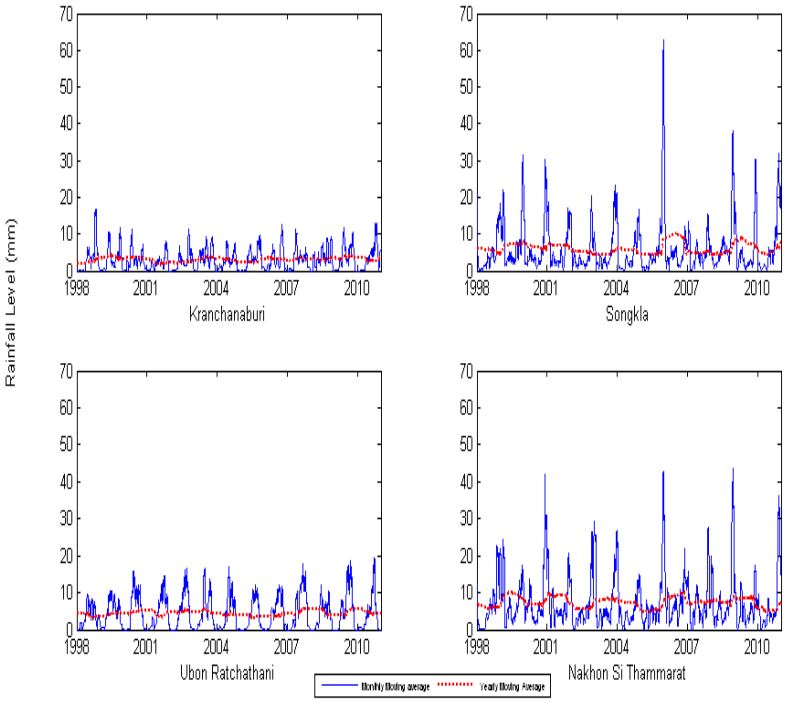


Figure C.2: The monthly moving average and yearly moving moving average unconditional probability of all weather stations

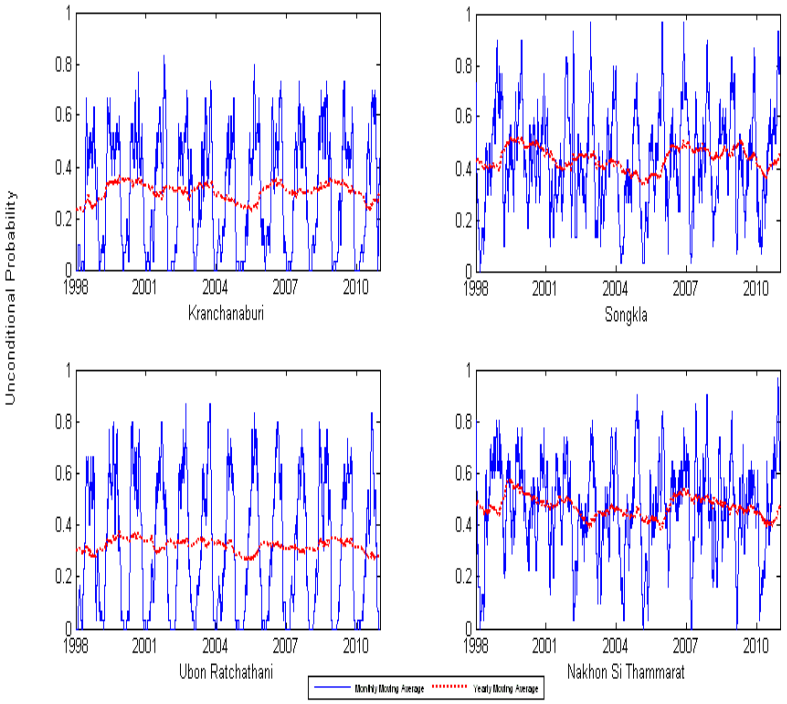
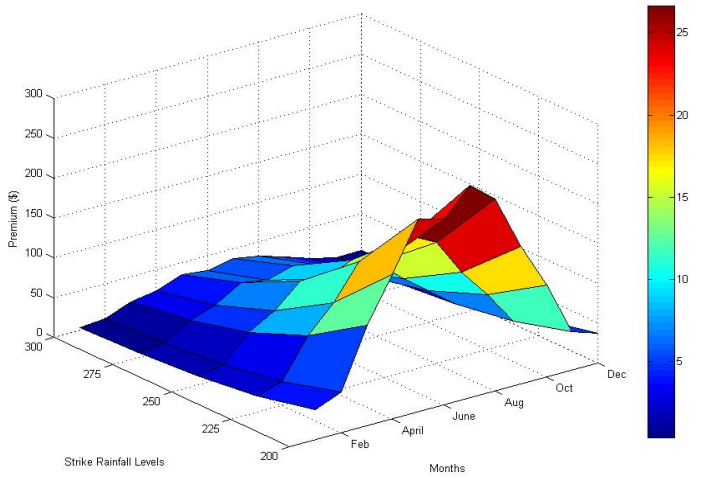


Figure C.3: Monthly insurance premium of constant strike rainfall levels interval of Ubon Ratchathani

- HR Index-Insurance Premium




- LR Index-Insurance Premium

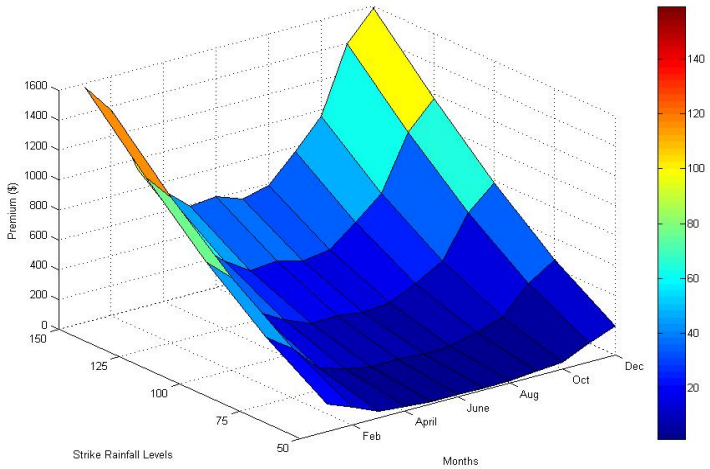
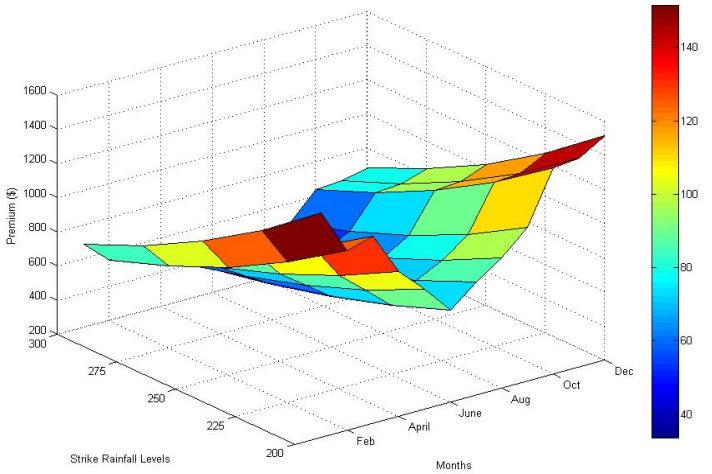


Figure C.4: Monthly insurance premium of constant strike rainfall levels interval of Songkla

- HR Index-Insurance Premium




- LR Index-Insurance Premium

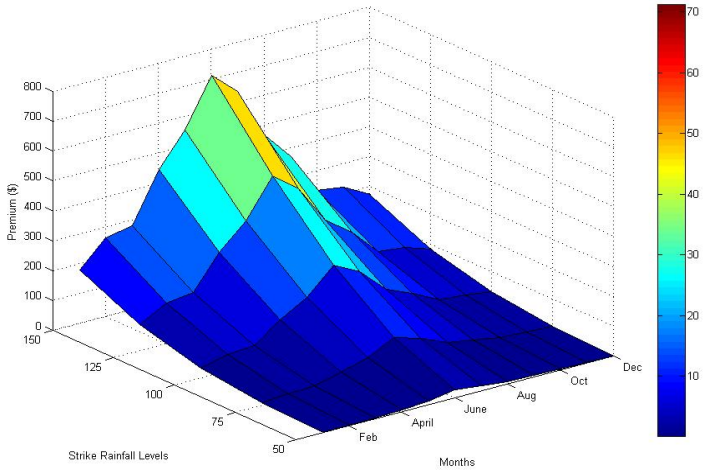
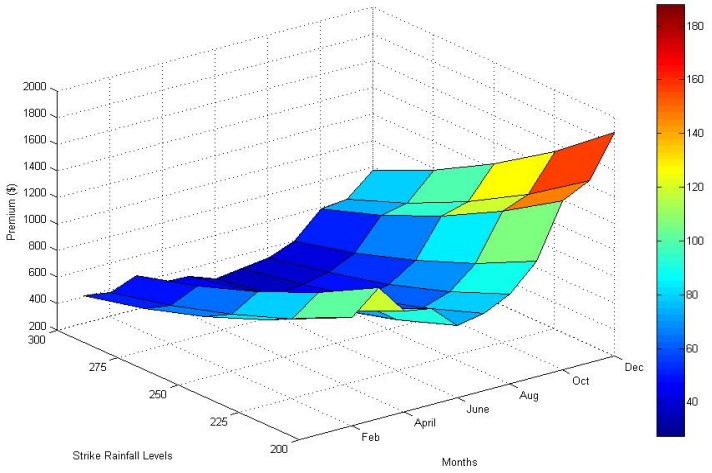


Figure C.5: Monthly insurance premium of constant strike rainfall levels interval of Nakron Si Thammarat

- HR Index-Insurance Premium




- LR Index-Insurance Premium

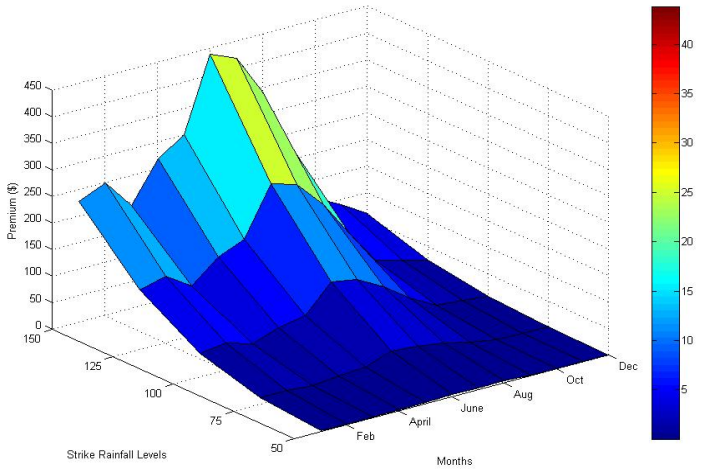
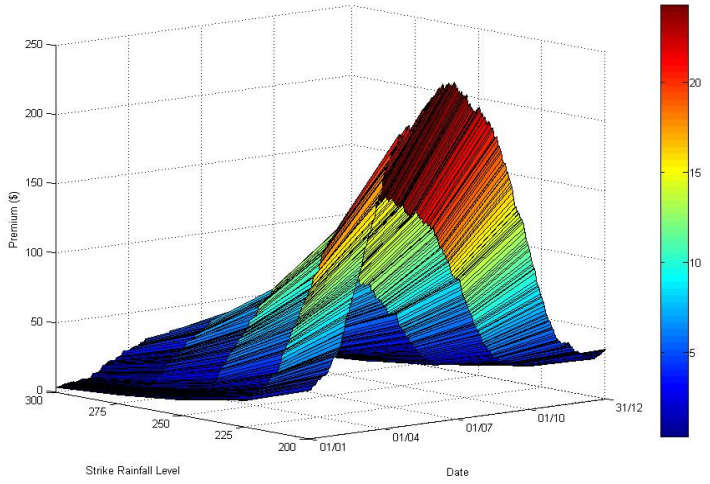


Figure C.6: 30-days insurance premium of constant strike rainfall levels interval of Ubon Ratchathani

- HR Index-Insurance Premium




- LR Index-Insurance Premium

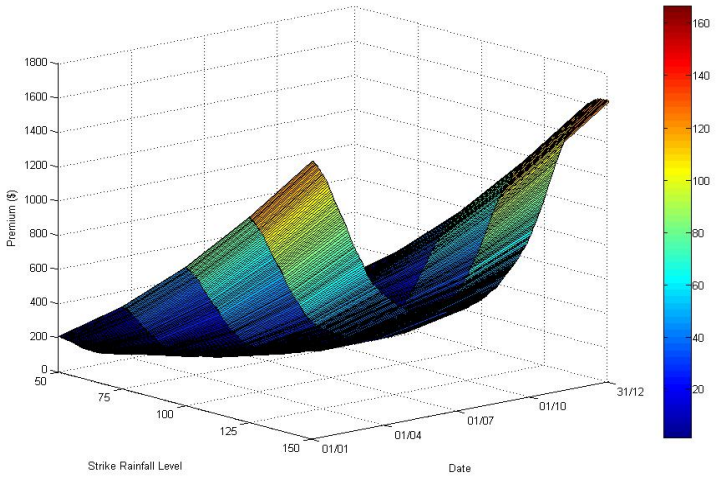
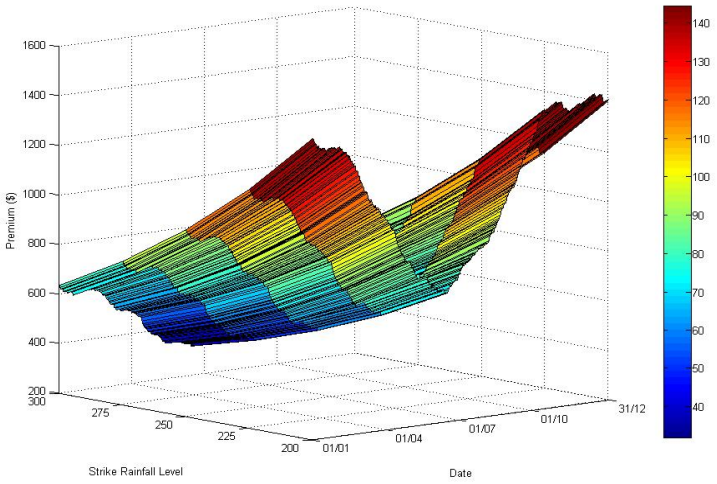


Figure C.7: 30-days insurance premium of constant strike rainfall levels interval of Songkla

- HR Index-Insurance Premium




- LR Index-Insurance Premium

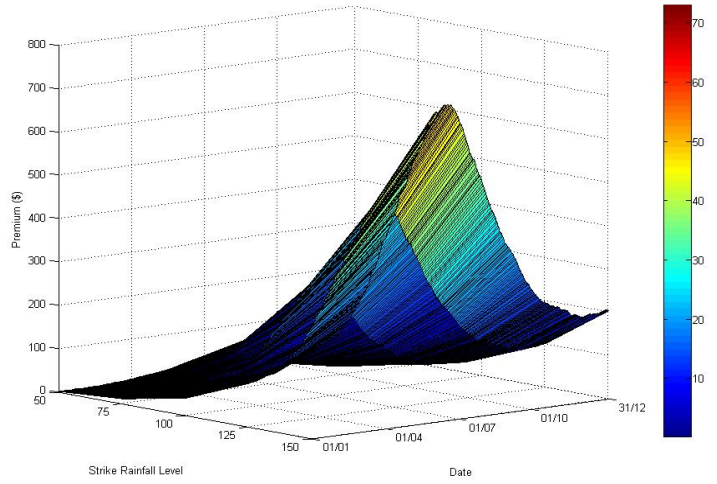
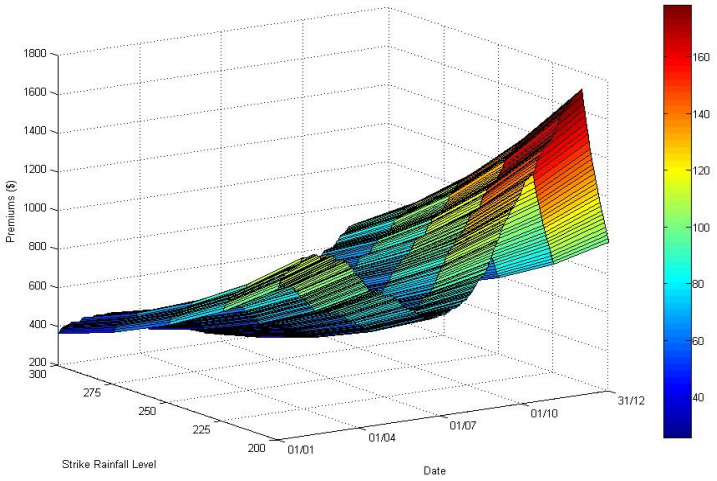


Figure C.8: 30-days insurance premium of constant strike rainfall levels interval of Nakron Si Thammarat

- HR Index-Insurance Premium




- LR Index-Insurance Premium

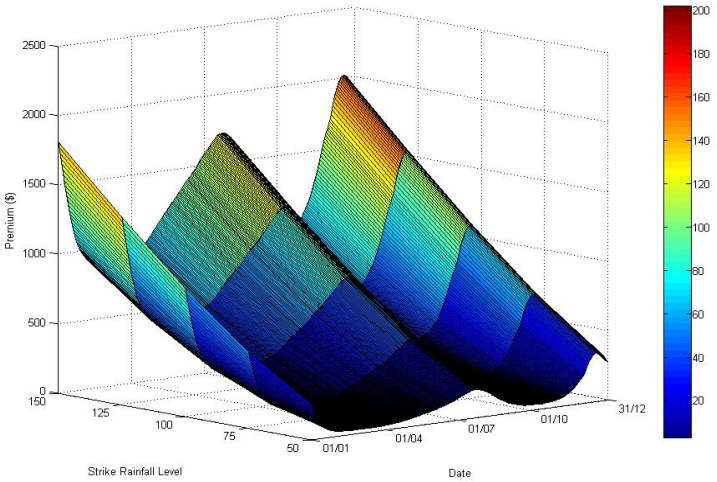
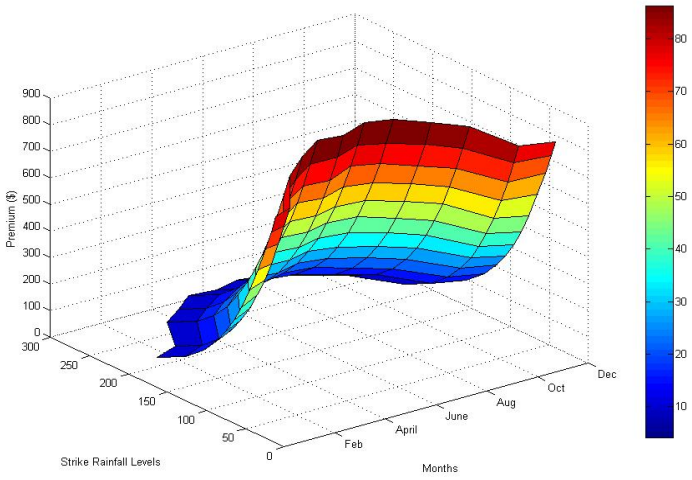


Figure C.9: Monthly insurance premium of seasonal strike rainfall levels interval of Ubon Ratchathani

- HR Index-Insurance Premium




- LR Index-Insurance Premium

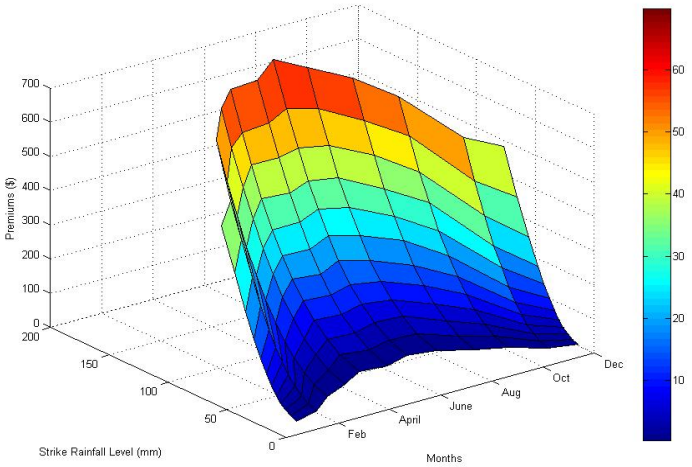
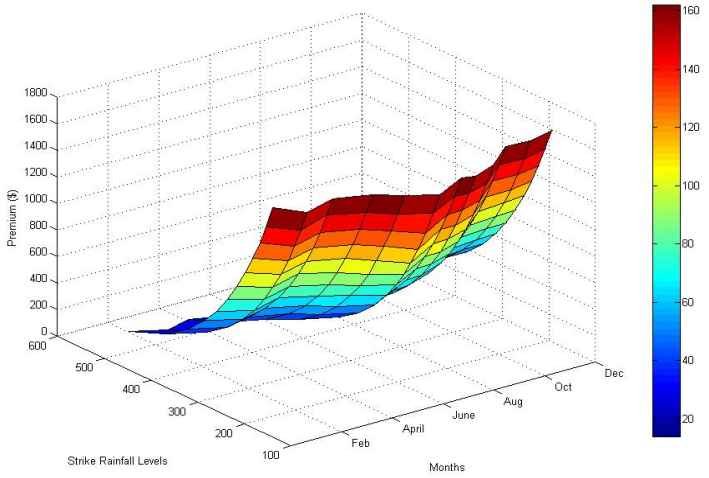


Figure C.10: Monthly insurance premium of seasonal strike rainfall levels interval of Songkla

- HR Index-Insurance Premium




- LR Index-Insurance Premium

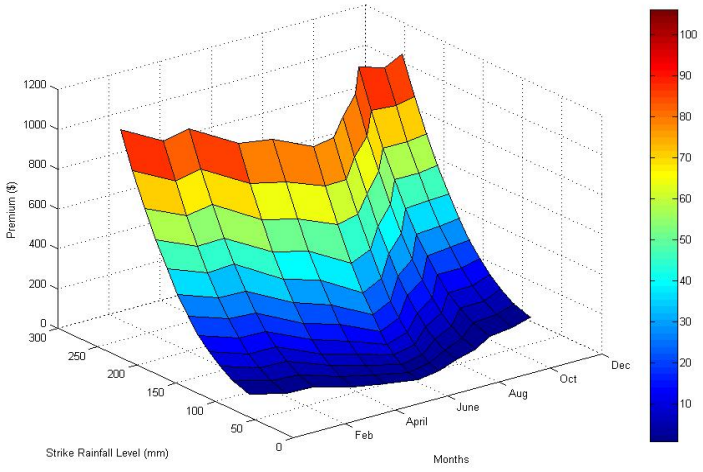
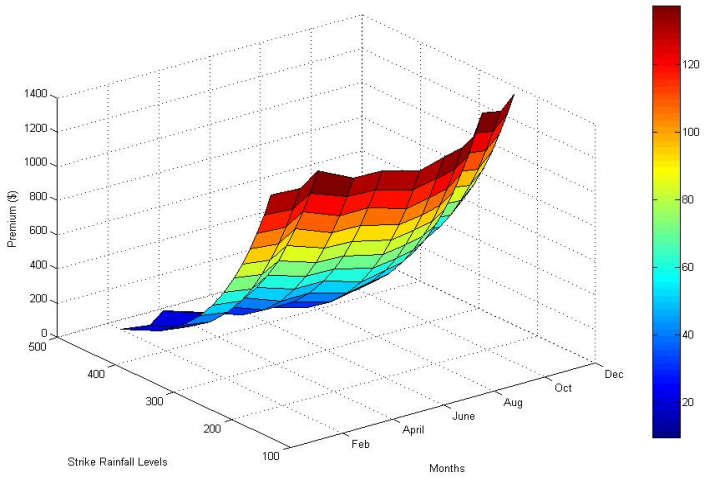


Figure C.11: Monthly insurance premium of seasonal strike rainfall levels interval of Nakron Si Thammarat

- HR Index-Insurance Premium




- LR Index-Insurance Premium

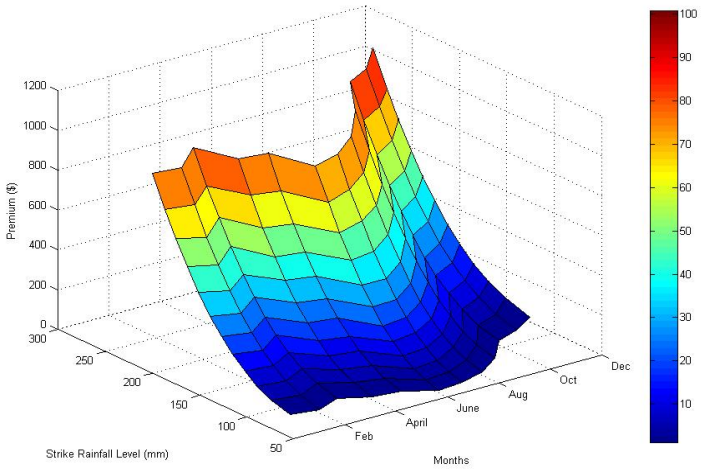
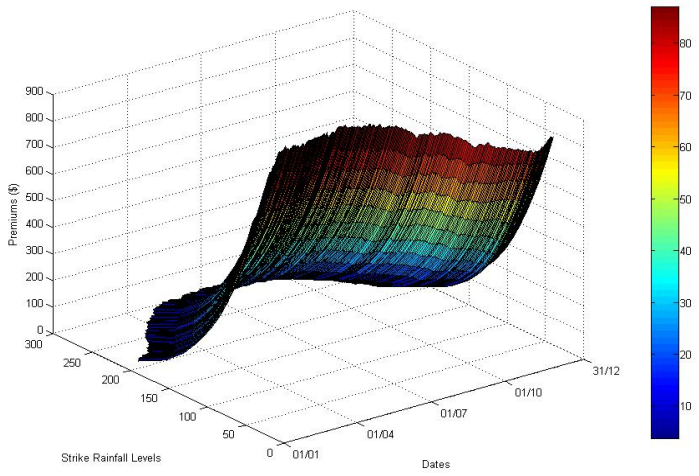


Figure C.12: 30-days insurance premium of seasonal strike rainfall levels interval of Ubon Ratchathani

- HR Index-Insurance Premium




- LR Index-Insurance Premium

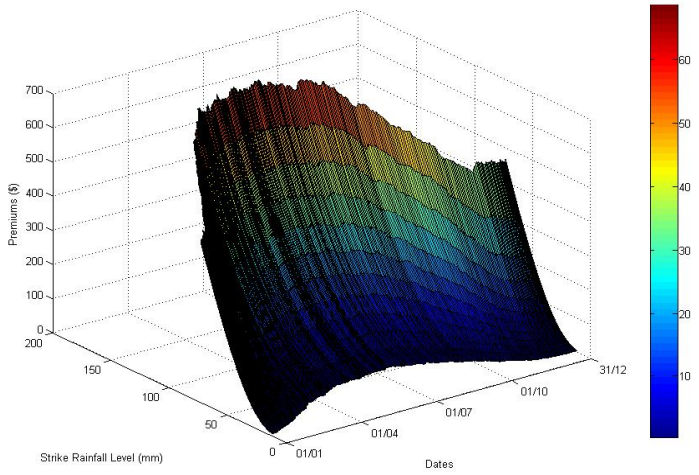
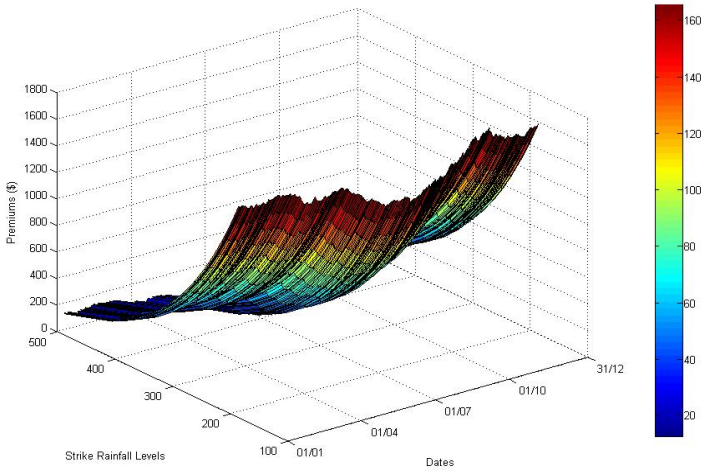


Figure C.13: 30-days insurance premium of seasonal strike rainfall levels interval of Songkla

- HR Index-Insurance Premium




- LR Index-Insurance Premium

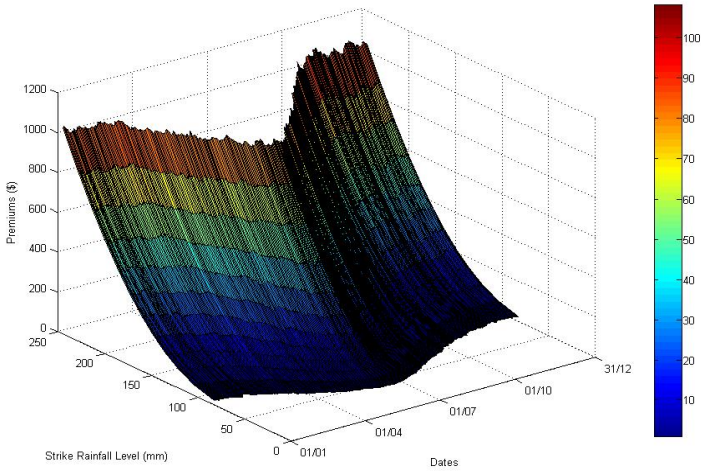
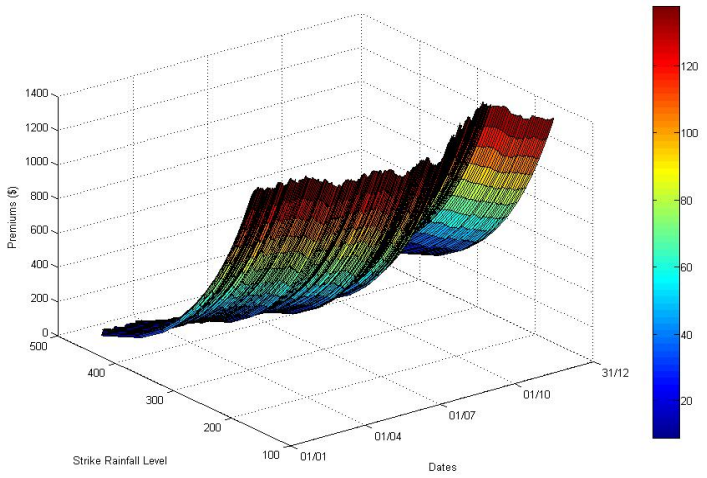


Figure C.14: 30-days insurance premium of seasonal strike rainfall levels interval of Nakron Si Thammarat

- HR Index-Insurance Premium




- LR Index-Insurance Premium

