



**ΕΘΝΙΚΟ ΜΕΤΣΟΒΙΟ ΠΟΛΥΤΕΧΝΕΙΟ
ΣΧΟΛΗ ΕΦΑΡΜΟΣΜΕΝΩΝ ΜΑΘΗΜΑΤΙΚΩΝ ΚΑΙ
ΦΥΣΙΚΩΝ ΕΠΙΣΤΗΜΩΝ**

ΔΙΑΤΜΗΜΑΤΙΚΟ ΠΡΟΓΡΑΜΜΑ ΜΕΤΑΠΤΥΧΙΑΚΩΝ ΣΠΟΥΔΩΝ

**«ΜΑΘΗΜΑΤΙΚΗ ΠΡΟΤΥΠΟΠΟΙΗΣΗ σε ΣΥΓΧΡΟΝΕΣ ΤΕΧΝΟΛΟΓΙΕΣ
και την ΟΙΚΟΝΟΜΙΑ»**

**«ΕΦΑΡΜΟΓΗ ΟΙΚΟΝΟΜΕΤΡΙΚΩΝ ΜΕΘΟΔΩΝ ΔΙΑΧΕΙΡΙΣΗΣ ΡΙΣΚΟΥ
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ΔΕΞΑΜΕΝΟΠΛΟΙΩΝ»**

ΕΠΩΝΥΜΟ ΟΝΟΜΑ ΜΕΤΑΠΤΥΧΙΑΚΟΥ ΦΟΙΤΗΤΗ:
ΓΚΟΛΦΙΝΟΠΟΥΛΟΣ ΑΛΕΞΑΝΔΡΟΣ

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ΤΡΙΜΕΛΗΣ ΕΠΙΤΡΟΠΗ:
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ΜΠΑΣΔΕΚΗΣ ΧΑΡΑΛΑΜΠΟΣ
ΧΡΙΣΤΟΠΟΥΛΟΣ ΑΠΟΣΤΟΛΟΣ

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ΠΕΡΙΛΗΨΗ

Η μεταβολή των τιμών των ναύλων αποτελεί μια σημαντική πηγή κινδύνου για όλους τους εμπλεκόμενους στις αγορές των ναυλαγορών δεξαμενόπλοιων, συμπεριλαμβανομένων των πλοιοκτητών, των ναυλωτών, των εμπόρων (traders), των τραπεζών, των Hedge Funds κλπ. Η εργασία αυτή ερευνά τον κίνδυνο της μεταβολής των ναύλων στις δύο πιο δημοφιλείς διαδρομές καθαρών φορτίων (διυλισμένα πετρελαιοειδή προϊόντα) και στις δύο πιο δημοφιλείς διαδρομές βρώμικων φορτίων (ακατέργαστο πετρέλαιο και βιομηχανικά καύσιμα), χρησιμοποιώντας ιστορικές τιμές από το Μάιο του 2007 μέχρι το Σεπτέμβρη του 2015 για τις διαδρομές TC2 και TD3 και από τον Απρίλιο του 2008 μέχρι το Σεπτέμβρη του 2015 για τις διαδρομές TC5 και TD7.

Η ανάλυση των αποδόσεων στις ναυλαγορές όψεως και προθεσμίας, υποδεικνύει ιστορικές κατανομές χαρακτηριζόμενες από υψηλές κορυφώσεις και συνωστισμένες άκρες. Ο καθορισμός μιας μεθόδου διαχείρισης κινδύνου που θα λαμβάνει υπόψιν της αυτά τα χαρακτηριστικά των κατανομών, κρίνεται μεγάλης σημασίας. Για την ποσοτικοποίηση του ρίσκου χρησιμοποιήθηκε η προσέγγιση Value at Risk (VaR), μια μέθοδος που αποφέρει αποτελέσματα εύκολα κατανοητά και γρήγορα επικοινωνήσιμα. Ένα ευρύ φάσμα παραμετρικών και μη παραμετρικών Value at Risk μεθόδων εφαρμόστηκε στις τιμές όψεως και προθεσμιακών συμβολαίων μελλοντικής εκπλήρωσης πλησιέστερου μήνα και πλησιέστερου τριμήνου και των τεσσάρων διαδρομών. Τα αποτελέσματα υποδεικνύουν σημαντικό κίνδυνο και στις τέσσερις διαδρομές. Η διαδικασία εξέτασης των αποτελεσμάτων (backtesting process) εκτελείται σε δύο βήματα. Στο πρώτο εξετάζεται η στατιστική σημαντικότητα των αποτελεσμάτων και στο δεύτερο εξετάζεται η οικονομική τους ακρίβεια. Σύμφωνα με τα αποτελέσματα, τα μοντέλα που θα πρέπει να χρησιμοποιούνται για τη διαχείριση του ρίσκου των ναυλαγορών δεξαμενόπλοιων είναι το απλό GARCH και τα μη παραμετρικά μοντέλα. Τα αποτελέσματα επαληθεύθηκαν και στις θέσεις ανόδου και στις θέσεις καθόδου.

ABSTRACT

The fluctuation of the freight rates (shipping freight risk) is an important source of risk for all participants in the tanker shipping markets including ship-owners, charterers, traders, hedge funds, banks, etc. This study examines the freight rate risk involved in the two most popular clean tanker routes (by clean meaning transportation of oil refined products) and two most popular dirty tanker routes (by dirty meaning transportation of crude oil or industrial fuel oil), using historical prices from May 2007 to September 2015 for the routes TC2 (Clean Route from Rotterdam to New York) and TD3 (Dirty Route from Ras Tanura to Chiba) and from April 2008 to September 2015 for the routes TC5 (Clean Route from Ras Tanura to Yokohama) and TD7 (Dirty Route from Sullom Voe to Wilhelmshaven).

The analysis of the historical returns of both spot and future prices reveals historical distributions with high peaks and fat tails. The establishment of a risk management method that could capture these distribution characteristics is of paramount importance. For the quantification of the risk, the Value at Risk approach is used, a method easily understood and communicated by all participants. A range of parametric and non-parametric Value at Risk methods is applied to the four routes spot, one month and three months front future price returns. The results suggest substantial freight rate risk at all four routes. The backtesting process of the Value at Risk models is conducted in two stages, with the first one by means of statistical accuracy of the results and the second one by means of economic accuracy. According to the results, the simple GARCH and non-parametric models should be preferred for risk management purposes, for both spot and future markets. The results are aligned between long and short positions.

TABLE OF CONTENTS

CHAPTER 1: INTRODUCTION.....	6
1.1 Aims and Objectives	8
CHAPTER 2: LITERATURE REVIEW	9
CHAPTER 3: THE TANKER MARKET.....	12
3.1 Wet Cargo	15
3.2 Chartering	16
3.3 Fixing on Spot or Time Charter	18
3.4 Charter Rates Drive Asset Prices	19
3.4.1 New build Values Driven by the Ship Building Cycle	19
3.5 Charter Rates and Utilization	20
3.5.1 Formation of spot rates is supply-demand equilibrium.....	20
3.5.2 High utilization drives charter rates higher	21
3.5.3 Utilization and Rates Not A Linear Relationship	21
3.6 World Scale	22
3.7 Freight Market Derivatives.....	24
CHAPTER 4: METHODOLOGY.....	27
4.1 Descriptive statistics.....	27
4.1.1 Distribution theory.....	27
4.1.2 Coefficient of kurtosis.....	29
4.1.3 Coefficient of Skewness	30
4.1.4 Jarque-Bera Normality Test.....	30
4.2 Value at Risk Methodology	31
4.2.1 Volatility estimation.....	32
4.2.1.1 Parametric Volatility Measurements	33
4.2.1.1.1 Rolling Window	33
4.2.1.1.2 Exponentially Weighted Moving Average (EWMA)	34
4.2.1.1.3 GARCH Model.....	34
4.2.1.1.4 EGARCH Model	36
4.2.1.1.5 Integrated GARCH (IGARCH) model	38
4.2.1.1.6 GJR-GARCH Model.....	38
4.2.1.1.7 The Power ARCH (PARCH) Model	39
4.2.1.1.8 Augmented GARCH Models	39
4.2.1.1.9 Distributional Assumptions.....	40
4.2.1.2 Non-Parametric Volatility Measurements	41
4.2.1.2.1 Historical Simulation (non – Parametric)	41

4.3 Backtesting	42
4.3.1 Statistical Accuracy.....	42
4.3.1.1 Kupiec's Unconditional Coverage (UC) Test	42
4.3.1.2 Christoffersen's Independence Test.....	43
4.3.1.3 Joint Test.....	44
4.3.2 Economic Accuracy.....	44
4.3.2.1 Loss Functions	44
CHAPTER 5: DATA	46
CHAPTER 6: EMPIRICAL WORK	48
6.1 Historical Distributions: Descriptive Statistics and Illustrations	48
6.2 Value at Risk Results	51
6.2.1 TC2	51
6.2.1.1 Spot	51
6.2.1.1.1 Value at Risk Statistics	52
6.2.1.1.2 Backtesting.....	53
6.2.1.2 FFA 1 Month.....	54
6.2.1.2.1 Value at Risk Statistics	55
6.2.1.2.2 Backtesting.....	56
6.2.1.3 FFA 3 Months.....	57
6.2.1.3.1 Value at Risk Statistics	58
6.2.1.3.2 Backtesting.....	59
6.2.2 TC5	60
6.2.2.1 Spot	60
6.2.2.1.1 Value at Risk Statistics	61
6.2.2.1.2. Backtesting.....	62
6.2.2.2 FFA 1 Month.....	63
6.2.2.2.1 Value at Risk Statistics	64
6.2.2.2.2 Backtesting.....	65
6.2.2.3 FFA 3 Months.....	66
6.2.2.3.1 Value at Risk Statistics	67
6.2.2.3.2 Backtesting.....	68
6.2.3 TD3	69
6.2.3.1 Spot	69
6.2.3.1.1 Value at Risk Statistics	70
6.2.3.1.2 Backtesting.....	71
6.2.3.2 FFA 1 Month.....	72
6.2.3.2.1 Value at Risk Statistics	73
6.2.3.2.2 Backtesting.....	74
6.2.3.3 FFA 3 Months.....	75
6.2.3.3.1 Value at Risk Statistics	76
6.2.3.3.2 Backtesting.....	77
6.2.4 TD7	78
6.2.4.1 Spot	78
6.2.4.1.1 Value at Risk Statistics	79

6.2.4.1.2 Backtesting.....	80
6.2.4.2 FFA 1 Month.....	81
6.2.4.2.1 Value at Risk Statistics	82
6.2.4.2.2 Backtesting.....	83
6.2.4.3 FFA 3 Months.....	84
6.2.4.3.1 Value at Risk Statistics	85
6.2.4.3.2 Backtesting.....	86
CHAPTER 7: CONCLUSION.....	87
CHAPTER 8: LIST OF REFERENCES.....	89
APPENDIX A	93
APPENDIX B (EVIEWS)	106

Chapter 1: Introduction

The purpose of this study focuses on establishing a framework which measures the level of the risk exposure for participants in physical and paper tanker freight markets. In order to develop and implement efficient and sound risk management methods, the tanker freight volatility should also be investigated. The price movement is represented by the worldscale's point fluctuations of four major tanker routes, with two of them represent the clean oil products trading and two represent the crude oil trading. For the purpose of this study, the author focuses on TC2, TC5, TD3 and TD7 routes. For each route the spot prices, the 1-Month front and the 3-Months (Quarter) front FFA prices are investigated. At the end of this thesis, the researcher offers suggestions on the most efficient Value at Risk methods for spot, 1-Month front and 3-Months font both in long and short positions, applied in all four routes. To the best of author's knowledge, it is the first time that a study compares the performance between parametric and non-parametric models in the tanker freight futures markets. Also, there are hardly any studies focusing on all market's participants by presenting results for both long and short positions.

The spot freight prices are determined through interaction of supply and demand for freight services. Freight markets are prevailed by conditions of perfect competition. The demand for wet freight services is inelastic as the freight cost represents only a small fraction of the price of the transported commodities. Indeed, the demand is affected by a numerous factors, such as world economic conditions, international seaborne trade, seasonality etc. Similarly, the supply is also affected by a numerous factors such as freight revenue, fleet productivity, shipbuilding production, scrapping levels and service speed.

Shipping freight prices are highly sensitive to shocks in supply and demand. Considering also the huge capital requirements, the seasonality, the sensitivity to the energy markets and the condition of the global economy, freight markets are

quite challenging for all participants. Thus, exploring and developing a risk management framework that could capture such peculiar conditions is of paramount importance.

Further in this study, the author focuses on measuring the tanker freight volatility, in order to establish a framework for measuring risk for all the participants in tanker freight markets, whether they are engaged in the physical or paper markets or if they are long or short. The tool that is used for risk measurement purposes, is the Value at Risk method (VaR), a highly used risk management instrument in the banking circles. In few words, Value at Risk informs the user about what is the largest loss that could experience with a certain probability. This method has gained a lot of attention due to its simplicity, making it easily communicated and understood.

The remainder of the paper is structured in the following order. As soon as the topic of this research has been introduced and the foundations of the study have been set, the author investigates the existed research that has been argued. More specifically, chapter two focuses on the literature review where secondary research is applied. Chapter three presents the «The Tanker Market» where the author provides information of the shipping industry and more precisely on how the tanker market operates. Furthermore, chapter four documents the methodology used in this study, which includes: value at risk methodology, non-parametric approach, parametric approach, distributional assumptions and back testing. Following, chapter five presents the data, chapter six the empirical analysis of the findings while chapter seven provides a reasonable conclusion with suggestions on best practice Value at Risk methods.

1.1 Aims and Objectives

In order to explore and develop a risk management framework, this thesis focuses on the historical distribution of freight rates in the shipping tanker market through a secondary research and examines the freight rate volatility using several parametric and non-parametric models.

Particularly, through a primary research this paper aims to provide a deep analysis by quantifying freight rate risk using Value-at-Risk methods where in order to support the evidences, the author back tests the Value-at-Risk using statistical tests. In conclusion, the study aims to offer the best models for each route in spot, 1-Month and 3-Month front for both long and short positions.

Chapter 2: Literature Review

Although Value at Risk methodology for assessing risk exposure has been adapted by many financial institutions and trading companies for many years, it has only been used in shipping very recently, following the growth in the forward freight agreements (FFA) market and the involvement of shipping companies in trading FFAs. As a result, research in the area of the application, relevance and importance of VaR in shipping and FFA markets has been very limited. The accurate calculation of VaR in freight rate markets is important as it will enable the market participants in the freight markets to quantify the freight rate risk that they are exposed to so as to develop effective hedging schemes subsequently. Additionally, it is very important to have knowledge of the possible extreme fluctuations of freight rates since freights are currently viewed as an alternative investment and thus it is urging to quantify the risk profile of this asset class. Lastly, VaR is frequently used to set the margin requirements in the fast developing freight exchange derivatives so as to ensure it grows even further. In the words of Angelidis and Skiadopoulos, "this is of particular importance given that freight derivatives, namely forward freight agreements (FFA's), freight futures and freight options, can be used to hedge freight rate risk" (Angelidis and Skiadopoulos, 2008, pp.449). In their study Angelidis and Skiadopoulos attempt to measure the risk for freight rates through a number of parametric and non-parametric approaches, as well as through adopting an Extreme Value Theory method, for four Baltic exchange indices. They notice that freight rate risk is higher in the tanker freight markets than in the dry freight sector, and conclude that the simplest non-parametric models are superior methods for calculating freight.

Abouarghoub attempts to measure Value at Risk for shipping freight rates of five dirty tanker routs by computing the following models FHS, GARCH-t(d) and EVT, and comparing the results with benchmarks such as HS and risk metrics. According to his research, the deployment of EVT could capture extreme non-normality and leverage effects (Abouarghoub, 2008).

Nomikos and Alizadeh in their work "Shipping Derivatives and Risk Management" presented for the first time a comprehensive methodology for the Value at Risk Estimation. The authors provide a complete and thorough overview of the practicalities of the shipping market. The methodologies include analysis and measurement of the impact of financial risks in shipping investments and the selection of the right strategies to mitigate relevant risks (Nomikos and Alizadeh, 2009).

Abouarghoub and Mariscal in their paper analyze freight volatilities for tanker freight returns, since they recognize it as a major issue for participants in freight markets. The understanding of freight volatility measures is vital in improving ship-owners profitability, and reducing financial risk exposure for investors and shipping portfolio managers. In detail, the study focuses in the five most liquid dirty tanker routes. They measure the risk exposure by using a non-parametric and a parametric method based on a GARCH model structure combined with an extreme value approach to measure conditional volatility. They also introduce a two state regime markov-switching framework to investigate the possibility of two different volatility structures in shipping tanker freight markets. The authors conclude that FHS based methods produce the most accurate results and also that tanker freight volatility depends on high and low state, something that explains the volatility clusters. "The vast and growing shipping derivative markets provide the necessary hedging tools for ship-owners and charterers to manage their freight risk exposures, provided those exposures are fully-understood" (Abouarghoub and Mariscal, 2011, pp.23). Further on the literature, Kavussanos and Dimitrakopoulos focus on four dirty routes and two Baltic indices. They investigate the distributions of the indices and the routes and examine the volatility with the usage of several Value-at-Risk methods. They conclude that simpler risk measurement methods should be selected in preference to more complex methods for freight rates.

The thesis contributes to the literature by examining the performance of several parametric and non-parametric Value at Risk models, in capturing the risk of the shipping freight future tanker markets and attempts to establish a risk management framework for all its participants. Furthermore, contributes with

illustrations and characteristics of the distributions and examines the volatility of the spot tanker freight rates for a more recent time period compared to existing research.

Chapter 3: The Tanker Market

Tankers are ships that transport liquids, gases, or specialized items. In the shipping market these commodities are referred to as "wet cargos" while grain or coal are referred to as "dry cargos". In comparison, there are two major types of oil tankers; crude and product tankers. Crude tankers transport the various grades of crude oil, industrial fuel oil and some condensates while on the other hand, product tankers transport refined petroleum products such as gasoline, jet fuel and diesel.

Beyond the two major tanker sectors of crude and product there are multiple sub-sectors which are generally based on vessel size. The five major sub-sectors or also known as "asset classes" of crude tankers are classified as: Very Large Crude Carriers (VLCC), often referred to as supertankers given their size as the largest tankers in the world; Suezmaxes which are the largest vessels that can navigate through the Suez Canal; Aframaxes often used as utility vessels; Panamaxes with maximum beam of 32m and Handysize that are engaged in regional trades.

Oppositely, the product market has four asset classes: The Long Range 2 (LR2) which are equivalent in size to Aframaxes; the Long Range 1 (LR1) which are also referred to as the Panamax class; the Medium Range 2 (MR2); the Medium Range 1 (MR1) which are also referred to as the Handysize class and the recently built LR3 carriers, equivalent to Suezmaxes vessels. It is worth mentioning that the largest tankers in the world today are the ULCCs (ultra-large crude carriers) although the manufacturing stopped in 2003. Likewise, there are also small product carriers, however their volumes and trade patterns primarily serve niche markets.

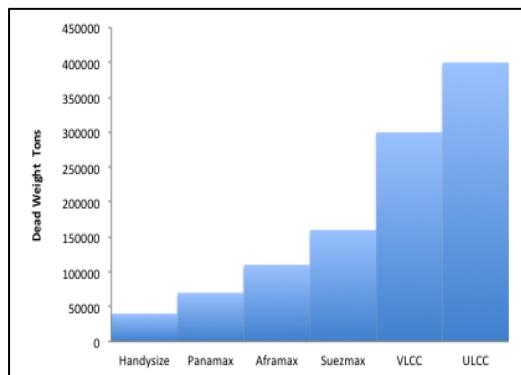


Figure 1: Crude Tankers Dwt (Source: Clarksons)

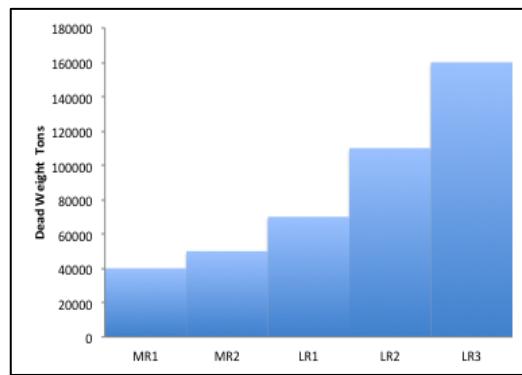


Figure 2: Product Tankers Dwt (Source: Clarksons)

Crude Tankers Crude oil is transported from production sites to refineries or terminals.

VLCC (~300,000 dwt) have a carrying capacity of ~2M barrels of crude oil and are typically used to transport oil from the Middle East and West Africa to Asia, North America, and Europe.

Suezmaxes (~160,000 dwt) have a carrying capacity of ~1M barrels of crude oil and are typically used to transport oil from West Africa and the Middle East to North America and Asia.

Aframaxes (~110,000 dwt) have a carrying capacity of ~700k barrels of crude oil and are most versatile of the major tanker classes due to their size. Aframaxes have accessibility to the majority of ports and waterways. Major trade regions for Aframaxes include the Caribbean, North Sea, Mediterranean, and intra-Asia.

Panamax (~70,000 dwt) have a carrying capacity of ~450k and are the largest vessels that can navigate the Panama Canal. Their beam is about 32 meters.

Handysizes (~40,000 dwt) have a carrying capacity of ~250k. Due to their LOA (Length over all) of less than 185 meters, these vessels can be facilitated by more ports than the remaining, something that engages them also in regional trades.

Product Tankers. Refined petroleum products are transported in smaller

quantities and product tankers have segmented tanks allowing the transportation of multiple cargoes. Refined products are transported from refineries and terminals to end users and terminals.

LR2s (~110,000 dwt) are the largest product tanker asset class and are classified as Aframaxes. LR2s are primarily used on long-haul product cargo voyages such as the Middle East to Far East.

LR1s (~70000 dwt) are also referred to as Panamaxes. LR1s are used for both long-haul and regional trades.

MR2s (~50,000 dwt) are the workhorse of industry and is by far the largest of the product tanker sub-sectors in terms of number of ships. The benchmark MR trade is from Europe to the US and is referred to as the TC2 voyage.

MR1s (~40,000 dwt) are typically used for short-haul trades.

Whether crude or product, tankers generally have a useful life of 20-25 years.

3.1 Wet Cargo

The major commodities carried on tankers are crude oil, from now-on referred as “crude” (unprocessed oil) and refined products (diesel, gasoline, fuel oil, heating oil, kerosene, jet fuel).

Likewise, product tankers are also classified as “Dirty” or “Clean” where Dirty include products such as fuel oil and crude oil while gasoline and jet fuel are classified as Clean. In addition, product tankers can be classified as chemical tankers that carry organics such as crude and natural gas derivatives; inorganics such as sulfuric and phosphoric acids, fertilizer, and edible oils such as palm and soybean oil. Whereas other specialized tankers carry asphalt and bitumen, fruit juice, methanol, waste, phosphoric acid, molten sulphur, and slop reception. Not surprisingly, the product tanker market is a traders market with arbitrage opportunities driving some cargo moves.

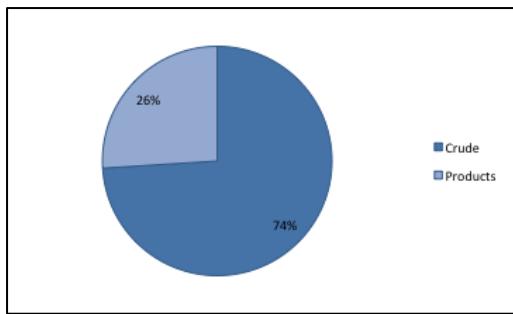


Figure 3: Seaborne Split Wet Cargoes (Source: Clarksons)

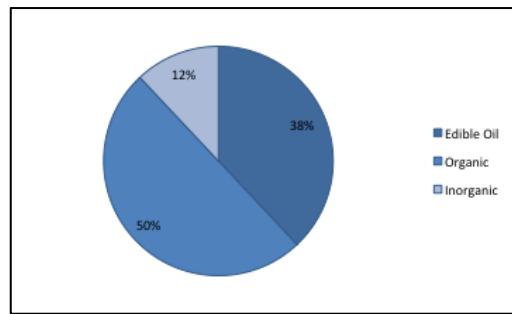


Figure 4: Seaborne Split Chemical Cargoes (Source: Clarksons)

3.2 Chartering

One of the main sources of income of ship owners is by charging customers for the transportation of crude and products cargoes. Contrariwise a ship broker mediates the details of the contract such as cargo, location, delivery date and the charter rate. While charterers or customers include National oil companies, major integrated oil companies, traders, refiners, governments, etc.

The three ways to employ a vessel are: on a spot charter, on a time charter, or on contract of affreightment (COA).

Spot Charters are short-term voyages (usually one trip) that capture current market pricing. At spot charters the ship owner pays voyage expenses (e.g fuel, port charges) and vessel operating expenses. The spot market is volatile and the most profitable in an up-cycle, tending ship owners wanting their vessels to be on the spot market in a rising market.

Time Charters are long-term contracts and tend to be less volatile than spot rates both on the downside and the upside. Unlike spot charters, charterers pay voyage expenses where ship owner pays vessel operating expenses. Time charters provide more stability of earnings and are more profitable than spot charters in a down cycle. For example, bareboat charter is a type of time charter where the charterer pays for both voyage and operating expenses with a fixed rate to the ship owner.

Contract of Affreightment (COA) is an agreement between a ship owner and a charterer for one or multiple cargoes whereby the owner provides a ship to the charterer for carry a specified amount of cargo over a stated time period. COAs benefit larger owners since they provide the guaranteed employment and flexibility. In addition, no vessel is specified and the delivery date(s) are flexible.

Indeed the methods of payment as well as the freight calculations and cost allocations vary depending on the type of charter contract agreed. As mentioned

above, for the spot charters the ship owner is responsible for the voyage costs, while for the time charters responsible is the charterer.

As Alizadeh and Nomikos state in their work, assuming that shipping freight markets are efficient, there should not be any difference between the discounted present value from an n period TC^n contract and the discounted present value earnings from a of spot voyage with n duration also (Alizadeh and Niminos, 2009).

$$\frac{TC^n}{(1+r)^i} = \frac{WS \times FR - VC}{(1+r)^i}$$

Equation 1: TC earnings should equal TCE earnings

For the purpose of comparing net operating earnings from TC contracts with net operating earnings from spot contacts, a TCE (Time Charter Equivalent) is calculated for the spot voyages.

$$\frac{WS \times FR - VC (Bunkers + Port Expenses + Broker Commissions)}{Voyage Days^1}$$

Equation 2: TCE calculation

¹ The voyage days are calculated from time of completion of last discharge operation of previous voyage to time of completion of last discharge operation of current voyage.

3.3 Fixing on Spot or Time Charter

As expected spot charters are more profitable and more volatile over the cycle assuming that more risk means more return. Undeniably, one of the most important factors that define the chartering strategy of ship owners is their expectation of the market. A bullish owner for example would most likely keep his fleet on spot to maximize exposure to a potentially rising spot market. On the other hand, a bearish owner would seek security of fixed rate charters to manage through a soft patch. At the same time, vessel operating costs are relatively fixed giving owners a high degree of operating leverage.

Additionally, while counter party risk is always a concern the two things benefit tanker charter contracts are: The UK law which gives customers little wiggle room in their contracts except for bankruptcy and the value of the cargo. For example, at today's oil price a VLCC customer would have to use the vessel 2,000 days at \$60k/d to equal the value of the crude on board.

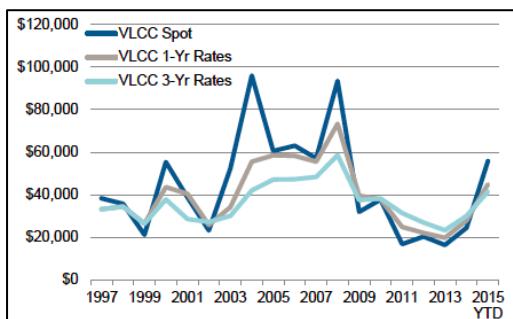


Figure 5: VLCC Charter Rates (Source: Clarksons, Credit Suisse)

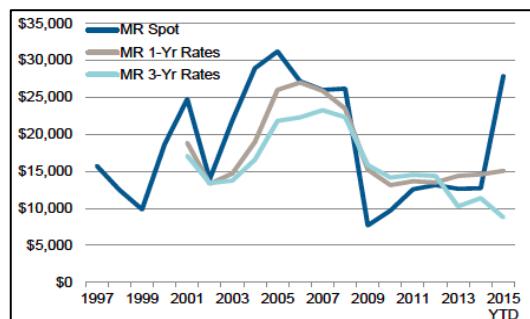


Figure 6: MR Charter Rates (Source: Clarksons, Credit Suisse, ICAP)

3.4 Charter Rates Drive Asset Prices

Usually the value of a ship is the value of its cash flows thus near term charter rates drive vessel values. Looking at figure 7, the 1-Yr VLCC time charter rate and 5-year old VLCC asset prices, the correlation is strong at 0.9. Also, as seen in figure 8 the correlation is also strong for MRs and the 1-Yr time charter rate and 5-year old prices with a correlation of 0.9. The correlation with spot rates and vessel values was also strong but below time charter rates owing to volatility.

3.4.1 New build Values Driven by the Ship Building Cycle

Similarly, charter rates drive second hand asset prices while the correlation between rates and new build prices is much weaker. That is because new build prices are more of a reflection of cost of production and the shipbuilding industry's pricing power. For example, turnaround time between ordering a ship and taking delivery of that ship is 24-30 months. Thus, the near term charter market has virtually no impact on a new build tankers earnings ability.

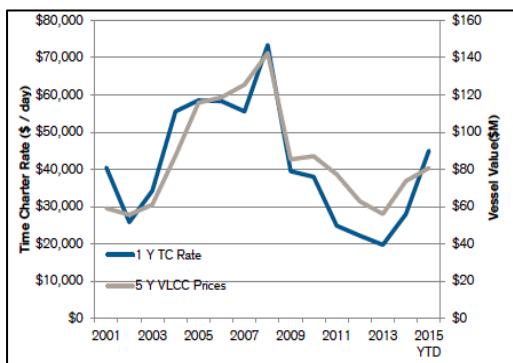


Figure 7: 1 year TC VLCC Rates and 5 year old VLLCC Prices (Source: Clarksons, Credit Suisse)

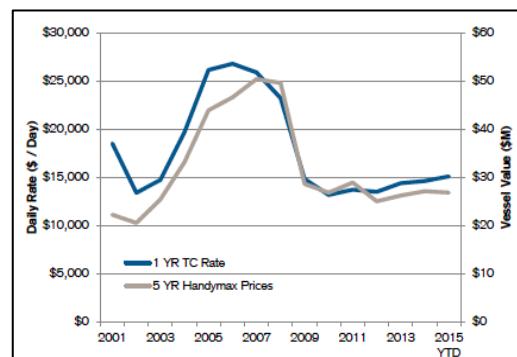


Figure 8: 1 year MR rates and 5 year old Prices (Source: Clarksons, Credit Suisse)

3.5 Charter Rates and Utilization

3.5.1 Formation of spot rates is supply-demand equilibrium.

As is commonly accepted, the industries' and markets' spot freight rates are dependent on supply and demand factors. The shipping industry considered as a global industry is affected by several factors worldwide, while various routes might be influenced differently by the same occurrence. Table 1 below, summarizes the most important factors affecting the supply and demand, and hence the formation of spot freight rates.

Demand	Supply
World Economy	World Fleet
Seaborne Commodity trades	Fleet productivity
Average haul	Shipbuilding production
Random shocks	Scraping and losses
Transport Costs	Freight Revenue

Table 1: Factors affecting Supply-Demand (Source: Stopford, 2009)

Although the Tanker's fleet utilization is difficult to track, the outcome gives an indication of the strength of the tanker market. However, most public companies often quote that their tanker fleet utilization range is up to 90% high even though it can be rather misleading since it does not capture the industry as a whole. On the other hand, vessels on time charter have 100% utilization for the vessel owner and this is because the owner is paid on a daily rate regardless of whether the vessel is on duty or not. However in the spot market the utilization is volatile, hence many of the larger tanker owners that focused on the spot market do not report utilization.

3.5.2 High utilization drives charter rates higher

The supply and demand balance is tight while there is a scarcity of ships (current status of the market). In up-cycles all ships regardless of quality, tend to find employment. On the flip side, on low utilization where there are too many ships but not enough cargoes, the charter rates drop. Likewise, weak markets see tonnage lay idle in search of work.

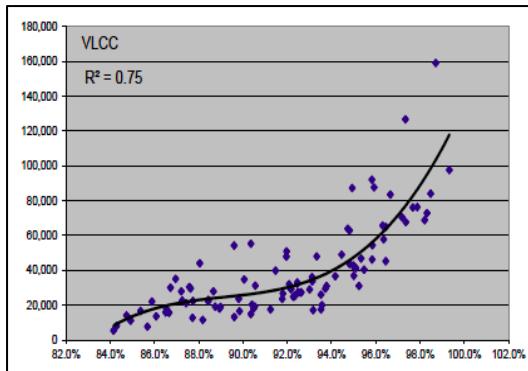


Figure 9: VLCC utilization versus spot rates
(Source: Marsoft, Credit Suisse)

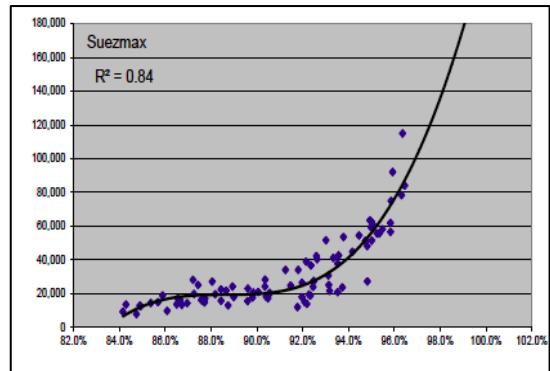


Figure 10: Suezmax utilization versus spot rates
(Source: Marsoft, Credit Suisse)

3.5.3 Utilization and Rates Not A Linear Relationship

It is worth mentioning that in late 2014 an increase in VLCC utilization drove spot charter rates to over \$70,000/d in November from \$10,000/d at the end of September. As a result, higher utilization can drive exponential spikes in charter rates. Nevertheless, utilization can also go down which could push spot rates lower quickly.

3.6 World Scale

World tanker nominal freight scale is usually referred to as "Worldscale". This is an index provided as a joint venture between two non-profit organizations, the Worldscale Association Limited (London) and the Worldscale Association Inc. (New York). Both companies are under control of a Management Committee, consisting of senior brokers from leading tanker broking firms in London and New York.

	TC2	TC5	TD3	TD7
2005	7.56	13.14	13.39	4.45
2006	8.52	14.19	15.16	4.74
2007	9.97	17.47	17.72	5.09
2008	10.2	17.8	18.05	5.4
2009	13.78	24.71	25.00	6.53
2010	10.53	18.42	18.72	5.59
2011	12.56	22.33	22.61	6.3
2012	14.95	26.65	26.95	7.11
2013	16.30	29.68	29.98	7.36
2014	15.48	27.85	28.13	7.73
2015	15.41	27.21	27.53	7.85

Table 2: Worldscale flat rate quoted as USD/mt per day (Source: Worldscale)

Based on Stopford study, Worldscale flat rate represents the cost of chartering a tanker for a specific voyage at a given period of time. Additionally, the flat rate is quoted in Worldscale 100, which is the price in dollars per ton for carrying oil at the given rate (Stopford 2009). When the spot price or contract is given in Worldscale points, it represents a percentage of the flat rate value. For instance, if the quoted price for TD3 is 65 Worldscale points it means 65% of the flat rate. If the flat rate is 10 USD/mt per day it means that the actual price per metric ton is $10 * 65\% = 6.5$ USD/mt per day. In order to obtain the amount of freight this rate has to be multiplied by the total tons of the cargo. If an FFA contact is the case, then actual contract value results from the product of this rate with the lot size and the number of lots.

In order for the flat rates to be calculated the following assumptions are taken into consideration:

World Scale	
Vessel	Panamax
Service Speed	14,5 knots
Bunkers Consumption	55 tons/day
Port Time	4 days
Canal Transit Time (PNM)	24 hrs
Canal Transit Time (SZ)	30 hrs
Bunker Price	Last year's avg prices

Table 3: Worldscale Flat Rate Assumptions (Source: Worldscale)

The flat rate is then calculated in order for the resulted TCE (Time Charter Equivalent) to equal \$ 12,000 per day.

Depending of the vessel size and the supply & demand equilibrium, the Worldscale points for a specific voyage are agreed accordingly. For example, a Panamax vessel with a voyage from Middle East Gulf to North Asia will be fixed with a higher Worldscale points from a VLCC due to the economies of scale that must favor the charterer of the second one. Similarly, if the demand for tanker transportation decrease within a year, the Worldscale points will be decreased also.

3.7 Freight Market Derivatives

Alizadeh and Nomikos state that “the derivatives market consists of financial instruments for trading in future levels of freight rates. The first exchange was established in the early 1980s. Ship owners, charterers and other parties involved in shipping wanted to apply the financial risk-management techniques, such as hedging using forwards, futures, swaps and options” (Alizadeh & Nomikos, 2009). This resulted in the first daily freight index, the Baltic Freight Index (BFI), published by the Baltic Exchange in January 1985. The BFI was first produced by a board of shipbrokers around the world, which gave their valuation of dry cargo routes. Traders could then buy or sell standardized contracts, known as futures contracts, for settlement against the BFI. All of the traders were registered with a clearinghouse and their portfolio was “marked to market” at the close of each trading day. The registration of trades with a clearinghouse was done in order to deal with the credit risk. “Since 1985 the derivatives market has developed, but the Baltic Exchange is still the leading exchange” (Alizadeh & Nomikos, 2009). Today there are more than 40 daily routes, forward prices, a sale and purchase index, fixture lists and market reports available at the Baltic Exchange.

Dirty Routes		
TD1	Ras Tanura (MEG) - LOOP (USG)	280k
TD2	Ras Tanura (MEG) - Singapore (SPORE)	260k
TD3	Ras Tanura (MEG)- Chiba (JPN)	260k
TD4	Off Bonny (WAF) - LOOP (USG)	260k
TD5	Off Bonny (WAF) - Philadelphia (USAC)	130k
TD6	Novorossiysk (BS) - Augusta (MED)	130k
TD7	Sullom Voe (NS) - Wilhelmshaven (CONT)	80k
TD8	Mina al Ahmadi (KWT) - Singapore (SPORE)	80k
TD9	Puerto la Cruz (CARIBS) - Corpus Christi (USG)	70k
TD10	Aruba (CRBS) - New York (USAC)	50k
TD19	Ceyhan (MED) - Lavera (MED)	80k

Table 4: Baltic International Tanker Dirty Routes

Clean Routes		
TC1	Ras Tanura (MEG) - Yokohama (JPN)	75k
TC2	Rotterdam (UKC)- New York (USAC)	37k
TC3	Aruba (CRBS) - New York (USAC)	30k
TC4	Singapore (SPORE)- Chiba (JPN)	260k
TC5	Ras Tanura (MEG)-Yokohama (JPN)	55k

Table 5: Baltic International Tanker Clean Routes

The shipping derivatives market is still a developing market and is characterized by low volumes in several routes. Tanker derivatives give a trader an opportunity to take a position in the tanker freight market. Derivatives then can be used to reduce the risk exposure to an existing position, or speculate to possibly increase profits. As seen on Alizadeh and Nomikos study, the tanker derivatives market contains several financial instruments, and Forward Freight Agreements (FFA) are the most frequently used derivatives in shipping today (Alizadeh and Nomikos, 2009).

In an attempt to define the FFA, Alizadeh and Nomikos described it as an “agreement between two counterparties to settle a freight rate or hire rate, for a specified quantity of cargo or type of vessel, for one or a basket of the major shipping routes in the dry bulk or the tanker market at a certain day in the future” (Alizadeh and Nomikos, 2009). The underlying asset of these contracts is a freight rate assessment for the appurtenant shipping route.

In the late 1990s FFA replaced futures contracts, which allowed the trader to customize the contract. The FFAs key feature are also known as principal-to-principal contracts, usually arranged by a broker. However, it can also be traded on screens provided by a number of freight derivatives brokers (Stopford, 2009). The arrangement of FFAs is similar to the way shipping has traditionally arranged time charters but no physical commitments are involved.

FFAs are traded either over-the counter (OTC) or through hybrid exchanges. The Figure

below presents the trading structure for the FFA market.

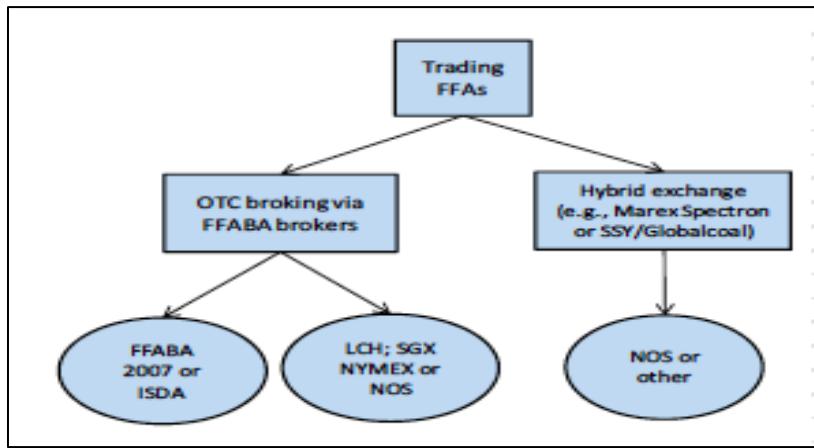


Figure 11: Trading structure for the FFA market (Source: Alizadeh & Nomikos, 2009)

The leading hybrid exchanges are Marex Spectron, previously International Maritime Exchange (IMAREX), SSY and Globalcoal, which all provide a marketplace for standardized FFAs. They are then cleared straight through the Norwegian Futures and Options Clearing House (NOS). Trades executed through Marex Spectron are known as “straight-through clearing”, which means that the trades are automatically cleared (Stopford, 2009).

The contract prices are quoted in Worldscale points. Equation 1 describes the calculation of the FFA contract value.

$$\text{Contract Value} = \text{No Lots} \times \text{Lot Size} \times \text{World Scale Flat Rate} \times (\text{Contract Price} \div 100)$$

Equation 3: Contract Value Calculation

Chapter 4: Methodology

4.1 Descriptive statistics

4.1.1 Distribution theory

The normal distribution has been extended used in academia although it is broadly known that the normal distribution theory does not hold in most of the real world situations. The reason is that distributions of the returns often have high peaks and fat-tails, a very important fact to consider when developing risk management methods.

There are many applications of the bell-shaped normal distribution. In fact, many variables will follow a normal distribution. If the price of an asset is log normally distributed the returns should be normally distributed, this is for example an assumption in the Black-Scholes-Merton option pricing formula. According to Bodie et al. the reasons why investment management is far more tractable when rates of returns are assumed to exhibit a normal distribution are the following:

1. The normal distribution is symmetric and the probability of any positive deviation above the mean is identical to a negative deviation of the same magnitude. Absent symmetry, measuring risk as the standard deviation of returns is inadequate.
2. The normal distribution belongs to a special family of distribution characterized as “stable” because when assets with normally distributed returns are used to construct a portfolio, the portfolio returns are also normally distributed.
3. Scenario analysis is greatly simplified when only two parameters (mean and standard deviation) need to be estimated to obtain the probabilities of future scenarios.

These three reasons are to “blame” for the popularity of the assumption that prices and returns are normally distributed, since they simplify investment and risk management

analysis. Nevertheless, has been empirically proved that high peak and fat tails do exist in the real world. Vilfredo Pareto was one from the first that looked at the fat-tailed distributions of income and developed an early theory for such distributions in the late 1800s (Haug, 2007). Pearson in his work introduced the idea that actual distributions differed from the normal distributions in terms of peakness, where Wesley C. Mitchell, on the other hand, was the first to empirically detect and describe fat-tailed distributions in price data in 1915.

Based on Mandelbrot and to the best of his knowledge, Oliver and Mills in their studies accordingly, were the first who provided the unquestionable evidence that empirical distributions of price changes are usually too “peaked” to be normally distributed (Mandelbrot, 1963). But then, in the late 1960s and early 1970s, several ground breaking models were published assuming that normal distribution existed in reality, although it had been proven otherwise already in the beginning of the 19th century. The distribution theory has however regained its attention in academia from the 1980s onwards. Researchers have attempted to develop normality tests against heavy tailed and high peaked distributions (Ruppert 1987; Bonett and Seier 2002; Gel, Miao and Gastwirth 2007; Gel ad Gastwirth 2008; Jarque and Bera 1980; Bowman and Shenton 1975), something that has contributed to enlighten the presence of fat-tails and high-peaks.

4.1.2 Coefficient of kurtosis

The coefficient of kurtosis, also known as the fourth moment of a variable around its mean, is a statistical measure used to describe the “peakness” of a distribution. The term of kurtosis originated from Greek, meaning bulging or convexity. Karl Pearson was the first to use the concept of kurtosis. The normal distribution is considered a mesokurtic distribution and has an estimated sample kurtosis of 3 (Karl, 1905). A distribution with a higher peak than a normal distribution's, also known as leptokurtic distribution, results a sample kurtosis >3. This practically means that very small and very large returns, are more likely to occur, in opposition to the medium-sized returns that are more frequently expected if K=3. On the other hand, if the sample kurtosis is <3, the sample distribution is relatively flat compared to the normal distribution. A flat distribution is also called a platykurtic distribution. Modern definitions of kurtosis acknowledge the fact that kurtosis will be influenced by both the peakness and the tail weight of a distribution and can be formalized in many ways (Ruppert 1987). However this thesis reports the Fischer kurtosis, also known as excess kurtosis (K-3). This is an adjusted version of the Pearson kurtosis, where a normal distribution has an estimated sample kurtosis of 0. The sample Fisher kurtosis is given by the following formula.

$$K = \left\{ \frac{n(n+1)}{(n-1)(n-2)(n-3)} \sum \left(\frac{x_i - \bar{x}}{\sigma} \right)^4 \right\} - \frac{3(n-1)^2}{(n-2)(n-3)}$$

Equation 4: Calculation of Fischer Kurtosis, where n is the number of observations

4.1.3 Coefficient of Skewness

The coefficient of skewness indicates whether or not the distribution of a sample or population is skewed around its mean. Except from kurtosis, Karl Pearson was also the first to introduce the term skewness (Pearson, 1895).

$$S = \frac{n}{(n-2)(n-3)} \sum \left(\frac{x_i - \bar{x}}{\sigma} \right)^3$$

Equation 5: Calculation of Skewness, where n is the number of observations

If the coefficient of skewness $S = 0$, the distribution of the sample is symmetric around its mean. It has been empirically observed in literature that actual distributions of returns are often slightly skewed to either the left or the right. If $S > 0$; the distribution is positively skewed with a majority of positive observations. On the other hand, if $S < 0$, the distribution is negatively skewed with a majority of negative observations.

4.1.4 Jarque-Bera Normality Test

The most broadly used normality test is the Bowman and Shenton statistic. The test derived by Carlos Jarque and Anil K. Bera also known as the Jarque-Bera Lagrangian Multiplier test or Jarque-Bera test (JB test), (Jarque and Bera, 1980). This is a goodness-of-fit test of whether a sample has kurtosis and skewness equal to the normal distribution of $K=0$ and $S=0$. However, the JB test and other classical normality tests do not necessarily work very well under all conditions and sample sizes. Although the JB test turns out to be superior in power to its competitors for symmetric distributions with relatively long tails, the test is poor for small samples, asymmetric distributions and distributions with short tails (Thadewald and Böning 2007; Mantalos 2010b). To overcome this problem different modifications or approaches to the JB test have been suggested. Mantalos in his study tested the power of these modifications on different sample sizes and concluded that his own method of creating robust “sample” critical values for the JB test is superior to the other evaluated tests for all sizes of samples (Mantalos, 2010a). Nonetheless there is no

available criticism in literature for his method. However, the research done by Mantalos shows that all tests perform well for large samples. Since, this thesis use more than seven years of daily data, the samples can be considered large enough. Hence, the JB-statistic is sufficient to test for normality.

$$JB = \frac{n}{6} (S^2 + \frac{1}{4} K^2)$$

Equation 6 : Calculation of JB, where K is the Fischer's Kurtosis, S is the Skewness and n is the number of observations

4.2 Value at Risk Methodology

Value at risk refers to maximum amount in money terms, which an investor is likely to lose over some period of time at a specific confidence level. In fact, Value at Risks are calculated from the 90th to 99.9th percentiles, depending for the reason are calculated for; in this thesis value at risks are calculated at the 90th, 95th and 99th confidence levels. VaR is estimated in the form:

$$VaR = SD \times Z_a$$

Equation 7: VaR Estimation

Where SD is standard deviation and Z is standardized returns, which are assumed to be i.i.d. $N(0,1)$. This thesis attempts to contribute in the study of modelling freight rate volatility and measure the risk exposure. Once, an appropriate forecast for standard deviation is calculated with one of the models that will be used, same is substituted in the Value at Risk formula to obtain one step ahead estimate of the maximum loss. Thus the value at Risk is computed using a two-step process. Firstly, an appropriate method is set up for estimating the conditional volatility and secondly a distribution assumption is used for the returns. This thesis uses the normal distribution, the Student's t distribution and the generalized error distribution to compute one day 1%, 5% and 10% Value at Risks estimates.

4.2.1 Volatility estimation

Volatility is one of the most important and widely used measures in finance, and the standard deviation of the returns is often used as a measure for the total risk of an asset (Brooks, 2008). Estimating volatilities is necessary for the valuation of derivatives and the calculation of Value-at-Risk. The simplest and the most straight forward way to estimate volatility is to calculate the historical constant variance and then the standard deviation of a sample or a population. However, the historical constant standard deviation is not a precise measure of the volatility (Hull, 2012). Mandelbrot was the first to discover and mention the phenomenon of volatility clustering. He noticed that a large price change tends to be followed by another large price change and vice versa (Mandelbrot, 1963). This discovery has inspired academics to investigate and model the behavior of variance in financial time series, and today it is a well-known fact that volatility is usually time-varying or stochastic (Alizadeh and Nomikos, 2009). Assuming constant volatility, may lead to incorrect estimates of the actual risk. Thus, it is important to deeply understand the volatility.

Over the past decades several volatility estimation models or methods have been developed. For instance, the Rolling Window, the Exponential Weighted Moving Average (EWMA) model, the GARCH and its extensions, and stochastic volatility models, with the last have been initially developed by Heston 1993; Hagan et al.2002; Bookstaber and Pomerantz 1989. However, there is no best-fit model for capturing the volatility in general. The empirical use of stochastic volatility models has been more limited due to difficulties attached to their estimation of their parameters (Alizadeh and Nomikos, 2009).

4.2.1.1 Parametric Volatility Measurements

4.2.1.1.1 Rolling Window

Klein in his study tried to capture the dynamics of the volatility of stocks using a Rolling Window, also called moving-window or moving-average-variance. This method is based on the most recent observations in a time series and detects if the volatility changes over time (Klein, 1977). For example, for a sample of 1,000 observations, the volatility can be estimated by calculating the standard deviation of the first 100 observations. One observation is then excluded at the beginning of the sample and one is included at the end. Continuing this way gives a continuous series of 901 observations with volatility for the 100 previous observations.

There are no firm rules concerning the choice of data sampling frequency or the number of lags to include (Andreou and Ghysels, 2002). The sampling frequency depends on the available time series and the research purpose. The Fama and MacBeths method that used monthly data and 60-month lags, has been widely used in academia. Another way is to use daily data and take monthly sums, using only returns within one calendar month (French, Schwert and Stambaugh, 1987). However, this method's resulted volatilities would be constant for each calendar month. The Rolling Window is not a very accurate method. Nevertheless, practitioners compute daily volatilities using this scheme applied to a daily and monthly sampling frequency, in order to provide an illustrative overview of the volatility and its variation over time (Alizadeh and Nomikos, 2009).

The most common parametric Value at Risk method that uses the rolling window volatility estimates is the model building approach.

4.2.1.1.2 Exponentially Weighted Moving Average (EWMA)

EWMA is estimated by the following equation

$$\sigma_n^2 = \lambda\sigma_{n-1}^2 + (1 - \lambda)\varepsilon_{n-1}^2$$

Equation 8: EWMA calculation (Source: Hull (2012) page 500)

Where σ^2 is the variance rate, ε is the daily percentage change in the variable and λ is a constant between zero and one. It has been proved that $\lambda=0.90-0.98$ is sufficient to capture the dynamics of time varying volatility, and in this thesis will be used $\lambda=0.94$, which is best suited for daily data and also used by Risk Metrics (Hull 2012, Alizadeh and Nomikos 2009).

4.2.1.1.3 GARCH Model

Engle at his work described ARCH as “a mean zero, serially uncorrelated processes with non-constant variances conditional on the past, but constant unconditional variances”. ARCH models can be very accurate in estimating time series volatilities (Engle, 1982). In addition, according to Danielsson the behavior of the time series is driven by three statistical characteristics (Danielsson, 2011):

1. volatility clusters
2. fat tails
3. nonlinear dependence

Following Mandelbrot and Nelson studies, they both defined volatility clustering as the phenomenon where large returns tend to be followed by large returns and small returns by small returns. Thus, periods of large returns are followed by periods of small returns and vice versa (Mandelbrot 1963; Nelson, 1991).

The distribution characteristic of fat tails practically means that large positive or large negative observations in financial data occur more frequently as compared to the standard normal distribution. Nonlinear dependence explains the relationship between multivariate financial data. For example, nonlinear dependence between different assets can be observed during financial crisis, where many assets are likely to move together in the same direction relevant to some market conditions (Danielsson, 2011).

Letting ε_t be a random variable, where in this thesis it is the World Scale rate time series expressed in daily returns, with a zero mean and variance conditional on the past time series. According to Engle ε_t is calculated as:

$$\varepsilon_t = \sigma_t z_t$$

Equation 9: Standardized Returns

Where z_t is a sequence of independent, identically distributed random variables with zero mean and unit variance. Typically, the distribution of z_t is assumed to be normal or leptokurtic (Terasvirta, 2006). However this thesis uses normal, Student and GED distribution assumptions that are analyzed in depth in the forthcoming parts.

The conditional variance of the ARCH model of order q is estimated by:

$$\sigma_t^2 = w + \sum_{i=1}^p a_i \varepsilon_{t-i}^2$$

Equation 10: Calculation of Arch (q), where $w>0, a_i>0$

Bollerslev suggested that generalized ARCH models, also known as the GARCH models (Bollerslev, 1986). The GARCH (q, p) is estimated by:

$$\sigma_t^2 = w + \sum_{i=1}^p a_i \varepsilon_{t-i}^2 + \sum_{i=1}^q \beta_i \sigma_{t-i}^2$$

Equation 11: Calculation of Garch (q, p)

For the calculation of the plain GARCH model, it is necessary to be imposed conditions, such as $w > 0$, $a_i > 0$, $\beta_i > 0$ and $\sum_{i=1}^p a_i + \sum_{i=1}^q \beta_i < 1$ in order positive, stationary and non-explosive conditional variance to be obtained. The significance of the parameter β_i indicates the dependence of the current value of the conditional variance on its lagged values. If the parameters of the lagged squared errors and variance are not statistically significant, then the variance in equation is constant.

The number of the lagged error p and variance q terms in the variance equation is called the order of ARCH (p) or GARCH (p, q) model.

This study uses GARCH models of orders $q=1$ and $p=1$ in estimating VaR for their simplicity and reliability that it offers, since it captures the dynamics of the variance quite adequately. GARCH (1, 1) is estimated by:

$$\sigma_t^2 = w + a_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2$$

Equation 12: Calculation of Garch (1, 1), where $w > 0$, $a_1 > 0$, $b_1 > 0$

4.2.1.1.4 EGARCH Model

Back in 1991 Nelson in order to overcome three main drawbacks of ordinary GARCH models introduced the exponential GARCH model (Nelson, 1991). The three main drawbacks that he had noticed were the following:

1. The negative correlation between current and future returns that GARCH models failed to incorporate in the assumptions
2. Necessary parameter restrictions
3. The fact that GARCH models were not recognizing and considering the asymmetric variance effects

According to Terasvirta thesis, EGARCH (q, p) is estimated by:

$$\log \sigma^2 = w + \sum_{i=1}^p [a_i \varepsilon_{t-i} + \lambda_i (|\varepsilon_{t-i}| - E|\varepsilon_{t-i}|)] + \sum_{i=1}^q \beta_i \log \sigma_{t-i}^2$$

Equation 13: Calculation of EGarch (q, p), where $a\varepsilon_{t-1}$ is a sign or asymmetry effect $\lambda_1(|\varepsilon_{t-1}| - E|\varepsilon_{t-1}|)$ is a magnitude effect

The functional form of the innovations, used in the model, allows the variance to respond differently to positive and negative shocks. So, if the coefficient of standardized residual is negative and significant, then negative shocks tend to increase the conditional variance and vice versa. The asymmetric effect of shocks with different sizes is captured by construction because the model is specified in exponential form. Thus, as long as the coefficient of the term which represents the difference between the size of the shock at time t and the expected value of the shock, is statistically significant, it indicates that larger than average shocks tend to increase the volatility relatively more compared to smaller than average shocks.

This thesis uses the EGARCH (1, 1) for simplicity and reliability reasons.

$$\log \sigma^2 = w + a_1 \varepsilon_{t-1} + \lambda_1 (|\varepsilon_{t-1}| - E|\varepsilon_{t-1}|) + \beta_1 \log \sigma_{t-1}^2$$

Equation 14: Calculation of EGarch (1, 1), where $a\varepsilon_{t-1}$ is a sign or asymmetry effect $\lambda_1(|\varepsilon_{t-1}| - E|\varepsilon_{t-1}|)$ is a magnitude effect

Where the part $\lambda_1(|\varepsilon_{t-1}| - E|\varepsilon_{t-1}|)$ constitutes the magnitude effect. Since the logarithm is always positive, EGARCH models do not need implied positivity constraints. Also asymmetry depends on the coefficient a. For instance, when $a < 0$, $\log \sigma_t^2$ would be greater than its mean w if $\varepsilon_{t-1} < 0$ and it would be smaller if $\varepsilon_{t-1} > 0$. This means that when $a < 0$ negative news have greater effects than positive news. On the other hand, when $a > 0$ positive news have larger effects on the conditional variance than negative news. This shows us typical asymmetry of the financial time series. The meaning of $E|\varepsilon_{t-1}|$ depends on the error distribution.

4.2.1.1.5 Integrated GARCH (IGARCH) model

Back in 1986 Engle and Bollerslev developed an extension of the GARCH model named the integrated GARCH (IGARCH) model. The IGARCH model restricts the sum of the parameters to equal to one which means that the return series is not covariance stationary and there is a unit root in the GARCH process (Jensen and Lange, 2007). Jensen and Lange noticed that “the conditional variance of the GARCH model converges in probability to the true unobserved volatility process even when the model is misspecified and the IGARCH effect is a consequence of the mathematical structure of a GARCH model and not a property of the true data generating mechanism” (Jensen and Lange, 2007). The restriction for IGARCH is

$$\sum_{i=1}^p [a_i] + \sum_{i=1}^q [\beta_i] = 1$$

IGARCH (1, 1) model:

$$\sigma_t^2 = w + a_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2$$

Equation 15: Calculation of IGarch (1, 1), where $w > 0$, $a_1 > 0$, $\beta_1 > 0$ and $a_1 + \beta_1 = 1$

4.2.1.1.6 GJR-GARCH Model

The GJR-GARCH was originally proposed by Gloste, Jagannatham and Runkle. where the model assumes to reveal and take into account the asymmetry property of financial data in obtaining the conditional heteroskedasticity (Glosten, Jagannathan and Runkle, 1993). They suggested augmenting the GARCH variance specification with a new term, which is dummy variable taking the value of 1 when shock is negative and 0 if the shock is positive.

The general form of the GJR-GARCH (q, p) is given by

$$\sigma_t^2 = w + \sum_{i=1}^p (a_i + \lambda_i I_{t-i}) \varepsilon_{t-1}^2 + \sum_{i=1}^q \beta_i \sigma_{t-i}^2$$

Equation 16: GJR-Garch (q, p), where $w > 0$, $a_1 > 0$, $b_1 > 0$, $\lambda_i > 0$ and $I_{t-1} = \begin{cases} 1, & \text{if } \varepsilon_{t-1} < 0 \\ 0, & \text{otherwise} \end{cases}$

In the above threshold GARCH (TGARCH) specification, when the shock is positive the coefficient of lagged error term is α_i and when the shock is negative the coefficient is $\alpha_i + \lambda_i$. Thus, the statistical significance of λ_i is regarded as evidence for asymmetric effect of

shocks with different signs of volatility. If coefficient λ_i is positive and significant then negative shocks tend to have greater impact on volatility compared to positive shocks with the same magnitude. But, if λ_i is negative and significant, positive shocks tend to have greater impact on volatility compared to negative shocks.

GJR-GARCH (1,1) model:

$$\sigma_t^2 = w + (a_1 + \lambda_1 I_{t-1}) \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2$$

Equation 17: GJR-Garch (1, 1), where $w > 0$, $a_1 > 0$, $b_1 > 0$, $\lambda_1 > 0$ and $I_{t-1} = \begin{cases} 1, & \text{if } \varepsilon_{t-1} < 0 \\ 0, & \text{otherwise} \end{cases}$

4.2.1.1.7 The Power ARCH (PARCH) Model

Taylor suggested the standard deviation GARCH model, where the standard deviation is modeled rather than the variance. Ding et al. in their paper generalized it with the Power ARCH specification (Ding et al. 1993). In the Power ARCH model the power parameter δ of the standard deviation is estimated and the optional γ parameters are added to capture asymmetry of up to order r :

$$\sigma_t^\delta = w + \sum_{i=1}^p a_i (|\varepsilon_{t-i}| - \gamma_i \varepsilon_{t-i})^\delta + \sum_{i=1}^q \beta_i \sigma_{t-i}^\delta$$

Equation 18: Calculation of PGarch, where $\delta > 0$, $|\gamma_i| \leq 1$ for all $i = 1, \dots, r$, $\gamma_i = 0$ for $i > r$, and $r \leq p$

The symmetric model sets $\gamma_i = 0$ for all i . For $\delta = 2$ and $\gamma_i = 0$ for all i , the PARCH model transforms itself to a simply a standard GARCH specification. The model captures the asymmetric effects for $\gamma \neq 0$.

APARCH (1,1) model:

$$\sigma_t^\delta = a_1 (|\varepsilon_{t-i}| - \gamma_i \varepsilon_{t-i})^\delta + \beta_1 \sigma_{t-i}^\delta$$

Equation 19: Calculation of PGarch (1,1), where $\delta > 0$, $|\gamma_i| \leq 1$ for all $i = 1, \dots, r$, $\gamma_i = 0$ for $i > r$, and $r \leq p$

4.2.1.1.8 Augmented GARCH Models

Leading market indicators like world economic growth, shipping related indexes etc. could be incorporated in models as an alternative method of including market conditions into

volatility. For instance a market indicator that could be incorporated in GARCH models is the slope of the freight forward curve (FFA Curve) or the term structure of freight rate. Alizadeh and Nomikos in their study investigate the relationship between the slope of the tanker freight forward curve and the volatility of FFAs using an augmented ARMA-TGARCH model of the following form

$$r_t = c_0 + \sum_{i=1}^m c_{1,i} r_{t-i} + \sum_{i=1}^m c_{2,i} \varepsilon_{t-1} + \varepsilon_t$$

$$\sigma_t^2 = w + (a_1 + \lambda_1 I_{t-1}) \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 + \gamma S L_{t-1}$$

Equation 20: Calculation of ARMA-TGarch X

Where $S L_{t-1}$ is the slope of the forward curve measured as the difference between the natural logarithm of the current month and fourth month FFA rates.

4.2.1.1.9 Distributional Assumptions

When working with ARCH models the distributions that assumed to be followed by the returns are mainly the following: the normal (Gaussian) distribution, the Student's t-distribution, and the Generalized Error Distribution (GED). In this thesis for each of the distribution assumptions, the ARCH models are estimated by the method of maximum likelihood.

For instance, for the GARCH (1, 1) model with conditionally normal errors, the contribution to the log-likelihood for observation t is:

$$l_t = \frac{1}{2} \log(2\pi) - \frac{1}{2} \log \sigma_t^2 - \frac{1}{2} (y_t - X_t' \theta)^2 / \sigma_t^2$$

Equation 21: Calculation of the log-likelihood with Normal Distribution assumption, where σ_t^2 is the conditional variance

For the Student's t-distribution, the log-likelihood contributions are of the form:

$$l_t = \frac{1}{2} \log\left(\frac{\pi(v-2)\Gamma(u-2)^2}{\Gamma((u+1)/2)^2}\right) - \frac{1}{2} \log \sigma_t^2 - \frac{(v+1)}{2} \log\left(1 + \frac{(y_t - X_t' \theta)^2}{\sigma_t^2(v-2)}\right)$$

Equation 22: Calculation of the log-likelihood with t-distribution assumption, where $v>2$ controls the tail behavior

For the GED, the log-likelihood contributions are of the form:

$$l_t = -\frac{1}{2} \log\left(\frac{\Gamma(1/r)^3}{\Gamma(3/r)(r/2)^2}\right) - \frac{1}{2} \log \sigma_t^2 - \left(\frac{\Gamma(3/r)(y_t - X_t' \theta)^2}{\sigma_t^2 \Gamma(1/r)}\right)^{r/2}$$

Equation 23: Calculation of the log-likelihood with GED Distribution assumption, where the tail parameter $r>0$. The GED distribution becomes normal for $r=2$ and fat tailed for $r<2$.

4.2.1.2 Non-Parametric Volatility Measurements

4.2.1.2.1 Historical Simulation (non – Parametric)

Historical Simulation is a resampling method that does not assume any particular distribution for the returns distributions, but rather uses the historical ones. The concept behind the inception of this model is that history repeat itself.

Suppose we observe data from day 1 to day t , and r_t is the return of portfolio on day t , then we get a series of return $\{r_{t+1-\tau}\}_{\tau=1}^m$. The value at risk at a confidence level p is calculated as the $(100p)\%$ of the sequence of past portfolio returns

$$\widehat{VAR}_{t+1}^p = \text{percentile}\{\{r_{t+1-\tau}\}_{\tau=1}^m, (100p)\%\}$$

Equation 24: Value at Risk estimation

The historical simulation is a non-parametric method that makes no specific distribution assumption about return distributions. This method also relies on the specified short historical moving window. This thesis estimates the Historical simulations 100 (using a rolling window of the past 100 daily returns), 250 (using a rolling window of the past 250 daily returns) and the full sample (including all observations up to day of calculated Value at Risk).

4.3 Backtesting

In order to assess the accuracy and performance of the Value at Risk models several backtesting methods have been developed. In the estimation process of Value at Risk models the confidence levels have to be included. Practically, for a model to work well it is expected that the times that actual returns exceed the value at risk estimations must equal to the chosen percentile of the out of sample observations. For instance, if a 99% confidence level is chosen, it is expected to find exceptions in 1% of the out of sample observations. In this thesis the several Value at Risk models are backtested using the Kupiec's unconditional test, the Christoffersen's independence test, the Joint test and the Quantile Loss Function. For a perfect Value at Risk model, the exception sequence should be independently distributed over time as a Bernoulli variable.

4.3.1 Statistical Accuracy

4.3.1.1 Kupiec's Unconditional Coverage (UC) Test

Kupiec's UC Test that is developed in his paper, is based on null hypothesis that empirically determined probability matches the given probability i.e.

$$\begin{aligned} H_0: p &= \hat{p} = \frac{x}{T} \\ H_1: p &\neq \hat{p} = \frac{x}{T} \end{aligned}$$

The null hypothesis is that observed failure rate \hat{p} is equal to the failure rate suggested by the confidence level. The Likelihood ratio test statistic is:

$$LR_{POF} = \left(\frac{(1-p)^{T-x} p^x}{\left[1 - \frac{x}{T}\right]^{T-x} \left(\frac{x}{T}\right)^x} \right)$$

Equation 25: Calculation of UC likelihood ratio, where T is the number of observations, x is the number of exceptions, c is the confidence level and p is the failure rate (1-c)

4.3.1.2 Christoffersen's Independence Test

Christoffersen's test not only covers the number of exceptions but considers also independence of them. In order for a model to be accurate, an exception at time t should not depend on whether or not an exception occurred on $t-1$.

H_0 : Exemptions are independent

H_1 : Exemptions are dependent

The test statistic is a likelihood ratio:

$$LR_{ind} = -2 \ln \left(\frac{(1 - \Pi)^{n_{00} + n_{01}} \Pi^{n_{01} + n_{11}}}{(1 - \Pi_0)^{n_{00}} \Pi_0^{n_{01}} (1 - \Pi_1)^{n_{01}} \Pi_1^{n_{11}}} \right)$$

Equation 26: Calculation of Ind likelihood ratio

Where, $\Pi_0 = \frac{n_{01}}{n_{00} + n_{01}}$, $\Pi_1 = \frac{n_{11}}{n_{10} + n_{11}}$ and $\Pi = \frac{n_{01} + n_{11}}{n_{01} + n_{00} + n_{10} + n_{11}}$. The n_{ij} is the number of days

when condition j occurred assuming that condition i occurred on the previous day.

$n(00)$ is no VaR violation at time I and on I-1 day.

$n(01)$ is no VaR violation at time I but there is VaR violation on I-1 day

$n(10)$ is VaR violation on time I but no VaR violation at time I-1 day

$n(11)$ is VaR violation at time I followed at other VaR violation at time I-1 day

Then π_i is the probability of observing an exception conditional on state i of the previous day

Where, $I_t = \begin{cases} 1, & \text{if violation occurs} \\ 0, & \text{if no violation occurs} \end{cases}$

If Π_0, Π_1 or Π equals to zero, then the independence test cannot be performed.

Both LR_{uc} Ratio and LR_{ind} Ratio are asymptotically Chi-squared distributed with one degree of freedom. If the value of LR_{uc} Ratio or LR_{ind} statistics exceeds the critical value of

the Chi-square distribution for given confidence level, the null hypothesis is rejected. The disadvantage of the unconditional test is that it measures only the number of exceptions and not their time dynamics. On the other hand, Christoffersen developed a test that could also be used to examine the independence of the exemptions.

4.3.1.3 Joint Test

The joint test statistic is calculated by combining Christoffersen's independence test with Kupiec's unconditional coverage test. With joint test is measured both the failure rate and the independence of the exceptions

$H_0: p = \hat{p} = \frac{x}{T}$ & the exemptions are independent

$H_1: p \neq \hat{p} = \frac{x}{T}$ & the exemptions are dependent

The test statistic is calculated by adding Christoffersen's independence test with Kupiec's unconditional coverage test:

$$LR_{CC} = LR_{uc} + LR_{ind}$$

Equation 27: Calculation of joint test

The Joint Test is asymptotically Chi-squared distributed with two degrees of freedom.

4.3.2 Economic Accuracy

4.3.2.1 Loss Functions

The statistical adequacy of the Value at Risks estimates can be captured with the analyzed tests. However, these statistical metrics cannot compare the models and only advice if accepted for the required confidence level. According to Lopez study, the author suggested to measure the accuracy of the Value at Risk estimates on the basis of the discrepancy between actual returns and Value at Risk estimates. For this purpose he suggested the Loss Function:

$$\Psi_{t+1} = \begin{cases} 1 + (y_{t+1} - VaR_{t+1|t})^2, & \text{if } y_{t+1} < VaR_{t+1|t} \\ 0, & \text{if } y_{t+1} \geq VaR_{t+1|t} \end{cases}$$

Equation 28: Calculation of LF Ψ_{t+1}

If the estimated Value at Risk did not capture the actual volatility at time t, then the Ψ_t equals 1 plus the difference between the observed return and the calculated, while if no violation is observed at time t, Ψ_t equals with 0. According to this metric, a model is preferred over another if it yields a lower total loss value, calculated as the sum of these penalties: $\Psi = \sum_{t=1}^T \Psi_t$. The Loss function incorporates both the cumulative number and the magnitude of exceptions. In comparison to Kupiec's binomial function, Loss Function adds up the magnitude term, so the larger the failure the higher the penalty. However, Loss function does not consider the discrepancy between the no violating value at risk estimates and the actual returns. The knowledge of whether a Value at Risk is overestimating the forecasted values it's quite useful for better allocation of resources. For this reason, this study uses a modified version of the Loss Function, called Quintile Loss Function as proposed by Angelidis, Benos and Degiannakis (Angelidis, Benos and Degiannakis, 2003).

QLF has the following form:

$$\Psi_{t+1} = \begin{cases} (y_{t+1} - VaR_{t+1|t})^2, & \text{if } y_{t+1} < VaR_{t+1|t} \\ [Percentile(y, 100p)]_1^T - VaR_{t+1|t}]^2, & \text{if } y_{t+1} \geq VaR_{t+1|t} \end{cases}$$

Equation 29: Calculation of QLF Ψ_{t+1}

Therefore at time t, Ψ_t equals either with the distance between the $VaR_{t+1|t}$ forecast and the 100p percentile of the historical return distribution, in case that the return is larger than the Value at Risk estimation, or by the excess loss $((y_{t+1} - VaR_{t+1|t})^2)$ term, if the realized return is smaller than the Value at Risk estimation. As with the Loss Function metric, a model will be preferred over another if it results the smaller amount.

Chapter 5: Data

The main goal of the thesis is to assess the capability of a number of alternative approaches to accurately capture the fluctuation of the freight for the main four tanker routes in both spot and futures markets (TC2, TC5, TD3, and TD7). As has already been stated, the freight spot and forward prices are quoted in Worldscale; a fraction of the flat rate. The full data sample is divided into an in-sample period, on which the model estimation section is based and an out-of-sample period over which Value at Risk performance is measured. The full data sample period for the routes TC2 (Clean Route from Rotterdam to New York) and TD3 TD3 (Dirty Route from Ras Tanura to Chiba) is from 22 May 2007 to 21 September 2015, while for the TD7 (Dirty Route from Sullom Voe to Wilhelmshaven) and TC5 (Clean Route from Ras Tanura to Yokohama) routes is from 24 April/2008 to 21 September 2015. The in-data sample period that used for the estimations for the routes TC2 and TD3 is from 22 May 2007 to 13 August 2013, while for the TD7 and TC5 routes is from 24 April 2008 to 7 November 2013. The out-of-sample period that used for the backtesting process is from 14 August 2013 to 21 September 2015 for the TC2 and TD3 routes, while for the TD7 and TC5 routes from 8 November 2013 to 21 September 2015. The period of the out-of-sample has been chosen in order to include both periods characterized by extreme returns like the financial crisis and periods characterized by returns close the average historical ones. Two different full sample periods used due to restricted availability of data for routes TC5 and TD7.

The data sample for the spot prices was downloaded from Clarkson Intelligence Network website, while the data sample for the one month and three months front future prices are provided from Baltic Exchange. All prices are expressed in World Scale.

For the purpose of this study, the author uses seven models of the ARCH family and three versions of the Historical Simulation in order to estimate the 1-day conditional variance, as presented and explained in the methodology section. Similar methodology has also been used by in the studies of Kavussanos and Dimitrakopoulos (2011), Angelidis and Skiadopoulos (2008) and Abouarghoub (2008). This study uses the Risk Metrics, GARCH (1, 1), IGARCH (1, 1), TGARCH (1, 1), EGARCH (1, 1), APARCH (1, 1) and an augmented

TGARCH (1, 1) that includes the slope curve of the difference between the spot and three months front prices. All GARCH family models have been estimated taking as an assumption for the standard returns the Normal, the Student's T and the Generalized Error Distributions. Except from the aforementioned parametric methods of calculating the conditional variance, this thesis uses also one non-parametric method, the Historical Simulation. Three Historical Simulation models are calculated here, the HS100 (based on the last 100 returns), the HS250 (based on the last 250 returns) and HSFS (based on the full Sample).

The estimation of the GARCH models has been performed using Maximum Likelihood Estimation (MLE) method, and was executed in Eviews program application. The Historical Simulations models are calculated in the excel program application.

In addition, the 1-day Value at Risk estimates have been calculated using the excel program application.

Finally, for the backtesting purpose, the 1-day Value at Risk estimates are compared with the actual 1-day returns. For the purposes of this thesis returns are computed in the following form:

$$R_{t+1} = \ln(S_{t+1}) - \ln(S_t)$$

Equation 30: Calculation of returns

Where S_t denotes spot price at time t and S_{t+1} spot prices at time t+1.

Both Kavussanos and Dimitrakopoulos (2011) and Angelidis and Skiadopoulos (2008) use tests to measure the statistical and the economic accuracy of their results. Both studies used an unconditional test, a conditional test, a joint test and the Loss function. Abouarghoub (2008) uses only statistical tests. This thesis uses the Kupiec's unconditional test, the Christoffersen's independence test, the Joint test and the Quintile Loss Function, with all of them have been estimated in the excel program application.

Chapter 6: Empirical work

This chapter is divided into two sections; one including the descriptive statistics of the raw data and returns along with a variety of illustrations and one including the Value at Risk results and their investigation. The selection process of the right model involves the evaluation of the backtesting results and the estimated coefficients. However, the used backtesting measures cannot compare different Value at Risk models directly. This is due to the fact that lower p-values do not indicate superiority of a model over another. For this reason, all models that results satisfying p-value scores are compared with each other using the Quintile Loss Function.

6.1 Historical Distributions: Descriptive Statistics and Illustrations

Table 6 presents the descriptive statistics for daily spot and future returns, for the shipping routes TC2, TC5, TD3 and TD7. Statistics are shown for full-samples. Full sample sizes are 2085 days for the TC2 and TD3 routes and 1855 days for the TC5 and TD7 routes.

Even though the excess skewness, the high kurtosis and the Jarque-Bera statistical scores clearly justify the non-normality of the distributions of all returns under investigation, the mean daily returns are quite close to zero, which clarifies the zero mean assumption. The autocorrelation of raw returns is also examined in order to test if the assumption of constant mean is valid. As presented in Figure 20 daily returns have very little autocorrelation. Evidence of volatility clustering is clear in graphs of daily returns in Figures 12, 13, 14 and 15 which suggest the presence of heteroscedasticity. These findings led to the adoption of the GARCH models discussed in the methodology section. Figures 16, 17, 18, 19 and 20 include graphs of QQ plots, returns, histograms and autocorrelations. All these combined with Figures 21, 22, 23 and 24 which plot the histograms against theoretical Normal distributions, demonstrate the defining characteristics of the tanker market; high volatility, seasonality, volatility clustering and fat-tailed distributions.

These characteristics further motivate the exploration of alternative approaches that could capture and incorporate tanker markets' peculiarities. Figures 21, 22, 23 and 24 which plot the histograms of past returns against a normal distribution curve, give an indication to what extent the histogram conform to the density of the normal distribution. In addition, they provide a portrayal of the returns' characteristics of the tanker freight markets; fatter tails and high peaks around zero than a normal's distribution. The fatter tails characteristic equal a higher probability of large losses than a normal distribution's. Excess skewness, if positive, means that the market exhibits large up moves but not equally large down moves and if negative vice versa. Such information could influence the shaping of trading strategies of the tanker markets participants.

(Please insert figures 12 – 24 about here)

Descriptive Statistics			Descriptive Statistics				
	TC2_Spot	TC2_1M	TC2_3M		TC5_Spot	TC5_1M	TC5_3M
Full Sample	22/MAY/2007-21/SEPTEMBER/2015			Full Sample	24/APRIL/2008-21/SEPTEMBER/2015		
In Sample	22/MAY/2007-13/AUGUST/2013			In Sample	24/APRIL/2008-7/NOVEMBER/2013		
Out of Sample	14/AUGUST/2013-21/SEPTEMBER/2015			Out of Sample	8/NOVEMBER/2013-21/SEPTEMBER/2015		
No of Obs	2085	2085	2085	No of Obs	1855	1855	1855
Mean	158.11	158.32	154.69	Mean	131.16	129.09	126.87
Median	146.67	146.50	141.50	Median	119.04	116.00	114.50
Maximum	386.25	353.00	305.00	Maximum	383.85	365.00	308.00
Minimum	9.55	80.00	91.00	Minimum	48.54	57.00	73.00
Std. Dev.	60.10	51.57	48.43	Std. Dev.	56.88	47.75	35.08
Skewness	1.33	1.21	1.23	Skewness	2.75	2.85	2.75
Kurtosis	4.99	4.03	3.57	Kurtosis	10.68	11.50	11.25
J-B	960.70	602.42	552.88	J-B	6894.66	8085.60	7598.04
Descriptive Statistics			Descriptive Statistics				
	TD3_Spot	TD3_1M	TD3_3M		TD7_Spot	TD7_1M	TD7_3M
Full Sample	22/MAY/2007-21/SEPTEMBER/2015			Full Sample	24/APRIL/2008-21/SEPTEMBER/2015		
In Sample	22/MAY/2007-13/AUGUST/2013			In Sample	24/APRIL/2008-7/NOVEMBER/2013		
Out of Sample	14/AUGUST/2013-21/SEPTEMBER/2015			Out of Sample	8/NOVEMBER/2013-21/SEPTEMBER/2015		
No of Obs	2085	2085	2085	No of Obs	1855	1855	1855
Mean	63.51	62.34	60.18	Mean	107.82	105.15	102.71
Median	52.28	54.00	51.59	Median	97.08	100.00	99.00
Maximum	319.22	215.00	180.00	Maximum	359.09	227.00	212.00
Minimum	25.36	30.00	30.50	Minimum	61.59	69.00	72.00
Std. Dev.	39.68	30.84	26.30	Std. Dev.	37.61	25.06	22.33
Skewness	2.92	2.31	2.02	Skewness	2.62	2.23	2.86
Kurtosis	12.85	9.04	7.67	Kurtosis	12.29	8.93	12.73
J-B	11394.58	5028.34	3312.13	J-B	8797.51	4263.61	9848.46

Table 6: Includes descriptive statistics for spot, 1 Month front and 3 Months front for TC2, TC5, TD3 and TD7 routes

6.2 Value at Risk Results

6.2.1 TC2

6.2.1.1 Spot

As per Table 6, TC2 spot returns' descriptive statistics indicate both excess kurtosis and skewness. More specifically the historical distribution is skewed on the right side (Fischer Skewness Statistic equals 0.52), which means that the market exhibits larger up moves than down moves. Same can be also confirmed by the study of the QQ plot on Figure 16 where it can be seen that the historical distribution deviates from the normal on the right side. Additionally, the distribution is leptokurtic with most of the returns being located around the average and on the tails. The autocorrelation test, which can be found on Figure 20 rejects any lagged correlation suspicion with all p-values equal to zero. The JB test clearly indicates distribution's non-normality.

Table 7, that includes the HIT sequences, suggests that both parametric and non-parametric models performed quite well for capturing the risk related to the long positions, with only exemption the VaR1% that have been calculated with parametric models assuming Generalized Error Distribution returns.

Considering all models' statistical accuracy, the shortlist concludes with the GARCH (1, 1)_N, IGARCH(1, 1)_N, IGARCH(1, 1)_T, EGARCH(1, 1)_N TGARCH(1, 1)_X_N, HS(250) and HS(FS) for long positions, while for short ones with the GARCH (1, 1)_N, IGARCH(1, 1)_N, IGARCH(1, 1)_T, EGARCH(1, 1)_N, HS(250) and HS(FS).

Nevertheless, considering also the auto-regression results the GARCH (1, 1)_N, TGARCH(1, 1)_X_N have being subtracted from the shortlist due to their statistical insignificance.

In terms of both statistical and economic accuracy, the models that should be selected for capturing TC2_S' risk for both long and short positions are the IGARCH(1, 1)_N, IGARCH(1, 1)_T, EGARCH(1, 1)_N and HS(250), with same to be in place for both long and short positions.

6.2.1.1 Value at Risk Statistics

TC2_S																		
Out of Sample Obs	Average VaR			Minimum VaR			Maximum VaR			Hit Sequence Long %			Hit Sequence Short %					
	526	1%	5%	10%	1%	5%	10%	1%	5%	10%	1%	5%	10%	1%	5%	10%	1%	5%
Model																		
GARCH (1,1)_N	-8.78%	-6.21%	-4.84%	-60.99%	-43.13%	-33.61%	-7.02%	-4.96%	-3.87%	1.14%	3.61%	7.79%	3.42%	5.51%	7.22%			
GARCH (1,1)_T	-33.96%	-24.00%	-18.69%	-422.84%	-298.84%	-232.75%	-7.02%	-4.96%	-3.87%	0.19%	0.38%	0.38%	0.19%	0.38%	0.95%			
GARCH (1,1)_GED	-6.72%	-6.17%	-5.48%	-79.11%	-72.62%	-64.55%	-3.49%	-3.20%	-2.85%	5.51%	6.08%	7.98%	6.08%	7.22%	7.41%			
IGARCH (1,1)_N	-8.31%	-5.88%	-4.58%	-11.56%	-8.17%	-6.37%	-6.70%	-4.74%	-3.69%	1.14%	4.18%	6.84%	4.18%	6.84%	7.79%			
IGARCH (1,1)_T	-9.00%	-6.36%	-4.95%	-36.09%	-25.50%	-19.86%	-2.11%	-1.49%	-1.16%	1.52%	4.94%	7.60%	3.61%	5.89%	8.37%			
IGARCH (1,1)_GED	-5.93%	-5.44%	-4.84%	-7.57%	-6.94%	-6.17%	-5.15%	-4.72%	-4.19%	3.99%	5.32%	6.65%	6.84%	7.03%	7.41%			
(GJR)TGARCH (1,1)_N	-8.72%	-6.17%	-4.81%	-42.59%	-30.12%	-23.47%	-6.50%	-4.60%	-3.58%	1.52%	5.32%	8.37%	2.85%	5.13%	7.03%			
(GJR)TGARCH (1,1)_T	-31.40%	-22.19%	-17.29%	-373.05%	-263.65%	-205.35%	-14.74%	-10.42%	-8.12%	0.19%	0.38%	0.38%	0.19%	0.57%	1.14%			
(GJR)TGARCH (1,1)_GED	-6.74%	-6.19%	-5.50%	-71.55%	-65.69%	-58.39%	-3.51%	-3.23%	-2.87%	5.70%	6.46%	8.17%	5.89%	6.84%	7.41%			
EGARCH (1,1)_N	-8.74%	-6.18%	-4.82%	-77.38%	-54.72%	-42.65%	-6.69%	-4.73%	-3.69%	1.52%	5.51%	8.56%	2.09%	5.32%	6.65%			
EGARCH (1,1)_T	-20.85%	-14.74%	-11.48%	-2144.37%	-1515.51%	-1180.37%	-8.45%	-5.97%	-4.65%	0.38%	0.57%	2.09%	0.95%	1.71%	2.66%			
EGARCH (1,1)_GED	-7.21%	-6.62%	-5.88%	-432.87%	-397.38%	-353.23%	-3.50%	-3.21%	-2.86%	6.08%	7.22%	8.75%	5.70%	6.08%	7.22%			
APARCH (1,1)_N	-8.47%	-5.99%	-4.67%	-18.35%	-12.97%	-10.11%	-2.50%	-1.77%	-1.38%	2.28%	6.65%	9.70%	2.47%	5.51%	7.60%			
APARCH (1,1)_T	-14.59%	-10.31%	-8.03%	-96.04%	-67.88%	-52.87%	-5.04%	-3.56%	-2.77%	0.57%	1.33%	3.42%	1.14%	2.09%	3.42%			
APARCH (1,1)_GED	-5.96%	-5.48%	-4.87%	-25.40%	-23.32%	-20.73%	-2.12%	-1.94%	-1.73%	5.70%	7.22%	8.56%	5.89%	6.46%	7.22%			
TARCH (1,1)_X_N	-8.73%	-6.17%	-4.81%	-42.41%	-29.99%	-23.37%	-6.55%	-4.63%	-3.61%	1.52%	5.32%	8.17%	2.85%	5.13%	7.22%			
TARCH (1,1)_X_T	-21.70%	-15.34%	-11.94%	-246.18%	-173.98%	-135.51%	-4.80%	-3.39%	-2.64%	0.19%	0.38%	0.76%	0.57%	1.33%	1.71%			
TARCH (1,1)_X_GED	-6.67%	-6.12%	-5.44%	-67.51%	-61.98%	-55.09%	-1.74%	-1.60%	-1.42%	5.51%	6.27%	7.03%	6.08%	6.65%	7.41%			
RISK METRICS	-16.45%	-11.63%	-9.07%	-211.23%	-149.39%	-116.42%	-3.19%	-2.25%	-1.76%	0.95%	4.37%	6.46%	3.42%	6.08%	7.41%			
HS(100) Long	-24.88%	-5.59%	-3.80%	-275.11%	-7.97%	-5.65%	-5.33%	-2.95%	-2.11%	1.52%	4.75%	11.03%	-	-	-			
HS(250) Long	-8.81%	-5.04%	-3.33%	-12.70%	-6.70%	-4.65%	-7.03%	-3.83%	-2.68%	1.14%	5.32%	11.98%	-	-	-			
HS(FS) Long	-7.92%	-4.35%	-2.99%	-8.39%	-4.60%	-3.12%	-7.32%	-4.20%	-2.92%	1.71%	8.17%	13.69%	-	-	-			
HS(100) Short	29.64%	7.44%	4.13%	9.54%	2.79%	1.52%	257.18%	12.93%	7.37%	-	-	-	1.14%	4.56%	9.51%			
HS(250) Short	14.11%	7.02%	3.32%	10.33%	4.26%	2.18%	15.75%	8.47%	4.68%	-	-	-	1.33%	5.51%	10.65%			
HS(FS) Short	11.22%	5.44%	3.33%	10.26%	5.37%	3.24%	12.31%	5.56%	3.43%	-	-	-	2.28%	7.03%	10.65%			

Table 7: Represents Value at Risk results for TC2 route spot price returns. The first column presents the different model types that used to measure Value at Risk. The next nine columns present average, minimum and maximum VaR estimates at 1%, 5% and 10%, confidence levels, respectively. The last six columns present the HIT sequence as a percentage of the out-of-sample observations. HIT sequences are reported for both long and short positions.

6.2.1.2 FFA 1 Month

As per Table 6, TC2 FFA 1 month front's descriptive statistics indicate kurtosis and slight skewness. The skewness is slightly positive (Fischer Skewness Statistic equals 0.09). As per Figure 20 the returns do not seem to have any serial autocorrelation, since all p-values equal to zero. The JB score even though indicates distribution's non-normality, it is far smaller than TC2_Spot's and TC2_3M's, with that meaning that TC2_1M's historical distribution is a better proxy of the normal distribution than TC2_Spot's or TC2_3M's historical distribution. Same is depicted from Figure 21 that plots the historical distributions against the theoretical normal distribution.

Tables 11 and 12 suggest that both parametric and non-parametric models performed quite well for capturing the potential losses related to the long positions, with only exemption the VaR1% that have been calculated with parametric models that assuming Generalized Error Distribution returns. In terms of statistical accuracy, the models that have been shortlisted for both long and short positions are the GARCH(1, 1)_N, GARCH(1, 1)_T, IGARCH(1, 1)_T, EGARCH(1, 1)_T, APARCH(1, 1)_T, TGARCH(1, 1)_X_T, HS(100), HS(250) and HS(FS). After filtering for models with significant and with persistence less than one coefficients, the shortlist of the parametric models concludes to the GARCH (1, 1)_N, GARCH (1, 1)_T, IGARCH(1, 1)_T, EGARCH(1, 1)_T, APARCH(1, 1)_T.

Comparing now the finalists in terms of economic accuracy, the model that scores the best at VaR1% is HS(FS), while for VaR5% and VaR10% are GARCH (1, 1)_N, GARCH (1, 1)_T and IGARCH(1, 1)_T. The results are confirmed from both long and short positions.

6.2.1.2.1 Value at Risk Statistics

TC2_1M															
Out of Sample Obs	Average VaR			Minimum VaR			Maximum VaR			Hit Sequence Long %			Hit Sequence Short %		
	526	1%	5%	10%	1%	5%	10%	1%	5%	10%	1%	5%	10%	1%	5%
Model															
GARCH (1,1)_N	-8.59%	-6.07%	-4.73%	-10.79%	-7.63%	-5.94%	-7.42%	-5.25%	-4.09%	2.47%	5.13%	8.94%	1.90%	4.75%	8.94%
GARCH (1,1)_T	-9.10%	-6.43%	-5.01%	-12.19%	-8.62%	-6.71%	-7.54%	-5.33%	-4.15%	1.71%	4.37%	7.22%	1.52%	3.99%	7.22%
GARCH (1,1)_GED	-6.07%	-5.58%	-4.96%	-9.91%	-9.10%	-8.09%	-4.96%	-4.55%	-4.05%	4.94%	6.46%	7.79%	5.13%	6.08%	7.98%
IGARCH (1,1)_N	-8.72%	-6.16%	-4.80%	-10.41%	-7.36%	-5.74%	-6.70%	-4.74%	-3.69%	2.09%	5.51%	8.17%	1.90%	4.37%	8.37%
IGARCH (1,1)_T	-8.83%	-6.24%	-4.86%	-10.87%	-7.68%	-5.98%	-6.63%	-4.69%	-3.65%	2.09%	5.32%	7.98%	1.90%	4.37%	7.79%
IGARCH (1,1)_GED	-5.89%	-5.40%	-4.80%	-6.56%	-6.02%	-5.35%	-5.07%	-4.65%	-4.14%	5.70%	6.46%	8.94%	4.37%	5.51%	8.17%
(GJR)TGARCH (1,1)_N	-8.66%	-6.13%	-4.78%	-10.15%	-7.18%	-5.59%	-7.63%	-5.40%	-4.20%	2.09%	4.94%	8.56%	1.71%	4.18%	8.37%
(GJR)TGARCH (1,1)_T	-9.15%	-6.47%	-5.04%	-22.74%	-16.07%	-12.52%	-7.93%	-5.60%	-4.36%	2.28%	4.94%	7.79%	1.71%	4.56%	7.98%
(GJR)TGARCH (1,1)_GED	-5.86%	-5.37%	-4.78%	-14.39%	-13.21%	-11.74%	-5.44%	-4.99%	-4.44%	5.70%	6.84%	8.94%	5.32%	5.89%	8.75%
EGARCH (1,1)_N	-8.96%	-6.33%	-4.94%	-10.37%	-7.33%	-5.71%	-7.31%	-5.17%	-4.03%	1.90%	4.56%	7.41%	1.71%	4.18%	7.98%
EGARCH (1,1)_T	-9.46%	-6.69%	-5.21%	-12.31%	-8.70%	-6.78%	-7.44%	-5.26%	-4.10%	1.33%	4.18%	7.03%	1.14%	3.99%	6.65%
EGARCH (1,1)_GED	-6.43%	-5.91%	-5.25%	-8.75%	-8.03%	-7.14%	-4.94%	-4.53%	-4.03%	4.75%	5.51%	6.84%	3.99%	5.13%	6.65%
APARCH (1,1)_N	-8.97%	-6.34%	-4.94%	-10.41%	-7.36%	-5.74%	-7.31%	-5.17%	-4.03%	1.90%	4.56%	7.41%	1.71%	4.18%	7.98%
APARCH (1,1)_T	-9.62%	-6.80%	-5.30%	-12.52%	-8.85%	-6.89%	-7.37%	-5.21%	-4.05%	1.52%	4.37%	6.84%	1.14%	3.80%	6.65%
APARCH (1,1)_GED	-6.54%	-6.00%	-5.34%	-8.62%	-7.91%	-7.04%	-5.35%	-4.91%	-4.36%	4.37%	5.13%	6.84%	3.80%	4.75%	6.65%
TARCH (1,1)_X_N	-8.61%	-6.09%	-4.74%	-10.69%	-7.56%	-5.89%	-7.42%	-5.25%	-4.09%	2.28%	5.13%	8.37%	1.90%	4.75%	8.56%
TARCH (1,1)_X_T	-9.15%	-6.46%	-5.03%	-22.90%	-16.19%	-12.61%	-7.91%	-5.59%	-4.36%	2.09%	4.94%	7.79%	1.71%	4.75%	7.98%
TARCH (1,1)_X_GED	-5.97%	-5.48%	-4.87%	-15.09%	-13.85%	-12.31%	-5.44%	-5.00%	-4.44%	5.70%	6.84%	8.37%	5.32%	5.70%	8.37%
RISK METRICS	-8.98%	-6.35%	-4.95%	-16.18%	-11.44%	-8.92%	-5.42%	-3.83%	-2.99%	2.28%	5.32%	8.37%	1.90%	4.56%	8.75%
HS(100) Long	-12.90%	-6.33%	-4.28%	-21.65%	-9.02%	-5.56%	-8.09%	-4.21%	-2.96%	0.76%	5.70%	11.41%	-	-	-
HS(250) Long	-13.76%	-6.08%	-3.98%	-16.45%	-9.28%	-4.92%	-11.87%	-5.31%	-2.84%	0.38%	5.51%	12.55%	-	-	-
HS(FS) Long	-11.09%	-5.06%	-3.58%	-11.12%	-5.25%	-3.69%	-11.01%	-4.92%	-3.42%	1.14%	7.60%	14.26%	-	-	-
HS(100) Short	12.47%	6.14%	4.38%	5.44%	3.36%	2.96%	20.91%	8.80%	5.58%	-	-	-	1.90%	5.70%	10.27%
HS(250) Short	10.09%	5.17%	4.09%	6.54%	3.92%	3.25%	12.85%	6.41%	5.02%	-	-	-	1.71%	7.03%	12.55%
HS(FS) Short	9.36%	4.98%	3.65%	9.21%	4.83%	3.47%	9.48%	5.10%	3.84%	-	-	-	1.33%	7.79%	14.64%

Table 10: Represents Value at Risk results for TC2 route 1-Month front FFA prices returns. The first column presents the different model types that used to measure Value at Risk. The next nine columns present average, minimum and maximum VaR estimates at 1%, 5% and 10%, confidence levels, respectively. The last six columns present the HIT sequence as a percentage of the out-of-sample observations. HIT sequences are reported for both long and short positions.

6.2.1.3 FFA 3 Months

As per Table 6, TC2 FFA 3 months front's descriptive statistics indicate negative skewness and kurtosis. The historical distribution is leptokurtic and skewed on the left side (Fischer Skewness Statistic equals -0.53). Looking on the Figure 16 that includes the QQ plots it can be clearly seen that some extreme returns are located on the right side of the normal distribution's diagram, a fact that illustrates the negative skewness. As per Figure 20 the returns do not seem to have any serial autocorrelation, since all p-values equal to zero. The JB test indicates distribution's non-normality.

Tables 14 and 15 suggest that the best performing models in terms of statistical accuracy are the GARCH (1, 1)_N, GARCH (1, 1)_T, EGARCH (1, 1)_N, EGARCH (1, 1)_T, HS(100), HS(250) and the HS(FS). Most of the parametric models were over-conservative resulting HIT sequences far below the confidence levels.

Non-parametric models superiority is supported in both terms of statistical and economic accuracy at 5% and 10% confidence levels. At 1% confidence level GARCH (1, 1)_N, GARCH (1, 1)_T and EGARCH (1, 1)_N performed better.

6.2.1.3.1 Value at Risk Statistics

Out of Sample Obs Model	526	TC2 3M														
		Average VaR			Minimum VaR			Maximum VaR			Hit Sequence Long %			Hit Sequence Short %		
		1%	5%	10%	1%	5%	10%	1%	5%	10%	1%	5%	10%	1%	5%	10%
GARCH (1,1)_N	-5.45%	-3.85%	-3.00%	-18.73%	-13.25%	-10.33%	-4.42%	-3.13%	-2.44%	1.33%	3.80%	6.08%	1.90%	3.99%	5.89%	
GARCH (1,1)_T	-7.20%	-5.09%	-3.97%	-10.96%	-7.75%	-6.03%	-5.85%	-4.13%	-3.22%	1.33%	1.90%	3.80%	0.95%	2.09%	2.85%	
GARCH (1,1)_GED	-2.79%	-2.56%	-2.28%	-7.25%	-6.66%	-5.92%	-2.13%	-1.96%	-1.74%	7.03%	7.98%	8.37%	7.03%	7.22%	10.46%	
IGARCH (1,1)_N	-5.09%	-3.60%	-2.81%	-7.58%	-5.36%	-4.18%	-3.02%	-2.13%	-1.66%	2.28%	4.56%	6.46%	2.28%	3.80%	6.46%	
IGARCH (1,1)_T	-5.13%	-3.63%	-2.82%	-7.75%	-5.47%	-4.26%	-3.00%	-2.12%	-1.65%	2.28%	4.56%	6.46%	2.47%	3.80%	6.08%	
IGARCH (1,1)_GED	-3.05%	-2.80%	-2.49%	-3.26%	-2.99%	-2.66%	-2.91%	-2.68%	-2.38%	5.51%	5.70%	7.60%	5.51%	6.27%	8.37%	
(GJR)TGARCH (1,1)_N	-5.46%	-3.86%	-3.01%	-28.50%	-20.16%	-15.71%	-4.19%	-2.96%	-2.31%	2.28%	3.99%	6.46%	2.66%	4.37%	7.03%	
(GJR)TGARCH (1,1)_T	-7.04%	-4.98%	-3.88%	-10.49%	-7.41%	-5.77%	-5.97%	-4.22%	-3.29%	1.33%	1.90%	3.80%	1.14%	1.90%	3.04%	
(GJR)TGARCH (1,1)_GED	-3.72%	-3.42%	-3.04%	-9.02%	-8.28%	-7.36%	-2.14%	-1.97%	-1.75%	4.75%	5.13%	6.08%	4.94%	4.94%	5.70%	
EGARCH (1,1)_N	-5.26%	-3.72%	-2.90%	-12.26%	-8.67%	-6.76%	-3.24%	-2.29%	-1.78%	1.90%	4.18%	7.22%	1.90%	4.94%	7.41%	
EGARCH (1,1)_T	-6.89%	-4.87%	-3.79%	-12.42%	-8.78%	-6.83%	-4.95%	-3.50%	-2.73%	1.52%	2.09%	4.56%	1.33%	2.28%	3.80%	
EGARCH (1,1)_GED	-2.77%	-2.54%	-2.26%	-7.91%	-7.27%	-6.46%	-2.56%	-2.35%	-2.09%	7.03%	7.60%	9.13%	6.27%	7.98%	9.51%	
APARCH (1,1)_N	-5.03%	-3.56%	-2.77%	-10.68%	-7.55%	-5.89%	-2.90%	-2.05%	-1.60%	2.85%	4.37%	7.41%	1.90%	5.13%	8.37%	
APARCH (1,1)_T	-7.68%	-5.43%	-4.23%	-14.23%	-10.06%	-7.83%	-4.96%	-3.51%	-2.73%	0.95%	1.90%	3.23%	0.95%	1.90%	2.85%	
APARCH (1,1)_GED	-3.12%	-2.87%	-2.55%	-7.15%	-6.56%	-5.83%	-2.49%	-2.29%	-2.03%	5.32%	6.46%	7.98%	5.51%	6.84%	7.60%	
TARCH (1,1)_X_N	-5.45%	-3.86%	-3.01%	-27.23%	-19.26%	-15.01%	-4.14%	-2.93%	-2.28%	2.28%	3.99%	6.46%	2.28%	4.37%	7.03%	
TARCH (1,1)_X_T	-7.03%	-4.97%	-3.87%	-10.44%	-7.38%	-5.75%	-5.91%	-4.17%	-3.25%	1.52%	1.90%	3.80%	1.14%	2.09%	3.23%	
TARCH (1,1)_X_GED	-3.00%	-2.75%	-2.44%	-6.76%	-6.21%	-5.52%	-2.45%	-2.25%	-2.00%	6.27%	7.03%	7.98%	6.08%	7.03%	8.17%	
RISK METRICS	-5.19%	-3.67%	-2.86%	-13.39%	-9.47%	-7.38%	-2.39%	-1.69%	-1.32%	2.85%	5.32%	7.03%	2.47%	4.56%	7.22%	
HS(100) Long	-9.32%	-3.49%	-2.15%	-14.81%	-6.80%	-4.07%	-3.11%	-1.53%	-1.35%	1.52%	5.13%	10.46%	-	-	-	
HS(250) Long	-8.44%	-3.18%	-1.84%	-12.38%	-4.24%	-2.59%	-4.84%	-1.93%	-1.51%	1.33%	5.70%	11.41%	-	-	-	
HS(FS) Long	-5.87%	-2.74%	-1.86%	-6.13%	-2.79%	-1.89%	-5.72%	-2.68%	-1.83%	1.71%	6.27%	10.84%	-	-	-	
HS(100) Short	9.52%	3.37%	2.25%	2.59%	1.96%	1.49%	16.11%	5.32%	3.64%	-	-	-	1.33%	4.75%	9.70%	
HS(250) Short	6.36%	2.94%	1.91%	3.14%	2.45%	1.47%	8.94%	4.41%	2.69%	-	-	-	2.09%	6.84%	11.22%	
HS(FS) Short	5.05%	2.80%	1.94%	4.88%	2.71%	1.92%	5.32%	2.87%	1.98%	-	-	-	2.09%	6.65%	11.60%	

Table 13: Represents Value at Risk results for TC2 route's 3-Months front FFA price returns. The first column presents the different model types that used to measure Value at Risk. The next nine columns present average, minimum and maximum VaR estimates at 1%, 5% and 10%, confidence levels, respectively. The last six columns present the HIT sequence as a percentage of the out-of-sample observations. HIT sequences are reported for both long and short positions.

6.2.2 TC5

6.2.2.1 Spot

As per Table 6, TC5 spot's historical distribution is leptokurtic and skewed on the left side (Fischer Skewness Statistic equals -2.28). Looking on the Figure 16 that includes the QQ plots, the negative skewness is being illustrated by the extreme returns that are located on the left of the normal distribution's diagram. As per Figure 20 the returns do not seem to have any serial autocorrelation, since all p-values equal to zero. The JB test clearly indicates distribution's non-normality.

According to Tables 16, 17 and 18 most of the parametric models are resulting over conservative results, with the HIT sequences being far below requested confidence levels. From Tables 17 and 18 , the remark that can be drawn is that no model passes all tests at all three confidence levels, however the models that passed the joint test at least at one confidence level are GARCH(1, 1)_T, GARCH(1, 1)_GED, IGARCH(1, 1)_N, TGARCH(1, 1)_T, TGARCH(1, 1)_GED, EGARCH(1, 1)_T, EGARCH(1, 1)_GED, APARCH(1, 1)_GED, TGARCH(1, 1)_X_T, HS(250) and HS(FS). Nevertheless, the list is narrowing after filtering for GARCH models with statistically significant coefficients. The only model from the shortlist that results significant coefficients is the EGARCH(1, 1)_T. Non-parametric models did not pass the joint test, however they all passed the unconditional test.

Comparing now the finalists in terms of economic accuracy, HS(250) and HS(FS) seem to be the best for TC5_S risk management's purpose, for both long and short positions.

6.2.2.1 Value at Risk Statistics

TC5_S																
Out of Sample Obs	Average VaR			Minimum VaR			Maximum VaR			Hit Sequence Long %			Hit Sequence Short %			
	465	1%	5%	10%	1%	5%	10%	1%	5%	10%	1%	5%	10%	1%	5%	10%
Model																
GARCH (1,1)_N	-4.56%	-3.22%	-2.51%	-18.77%	-13.28%	-10.35%	-3.98%	-2.81%	-2.19%	0.65%	1.94%	3.23%	0.43%	2.15%	5.16%	
GARCH (1,1)_T	-4.08%	-2.88%	-2.25%	-35.27%	-24.93%	-19.42%	-1.87%	-1.32%	-1.03%	1.51%	3.23%	6.67%	1.29%	3.23%	5.81%	
GARCH (1,1)_GED	-2.97%	-2.72%	-2.42%	-24.31%	-22.32%	-19.84%	-1.59%	-1.46%	-1.29%	2.80%	3.23%	3.87%	2.80%	3.01%	3.66%	
IGARCH (1,1)_N	-3.72%	-2.63%	-2.05%	-4.43%	-3.13%	-2.44%	-3.35%	-2.37%	-1.85%	1.29%	3.01%	5.38%	1.51%	6.88%	10.32%	
IGARCH (1,1)_T	-3.74%	-2.64%	-2.06%	-3.74%	-2.65%	-2.06%	-3.74%	-2.64%	-2.06%	1.51%	3.01%	4.95%	1.51%	6.45%	10.11%	
IGARCH (1,1)_GED	-2.75%	-2.53%	-2.25%	-2.76%	-2.53%	-2.25%	-2.75%	-2.52%	-2.24%	3.01%	3.23%	4.52%	6.02%	6.88%	9.25%	
(GJR)TGARCH (1,1)_N	-4.56%	-3.23%	-2.52%	-13.74%	-9.71%	-7.57%	-4.02%	-2.84%	-2.22%	0.65%	2.37%	3.44%	0.43%	1.72%	4.30%	
(GJR)TGARCH (1,1)_T	-4.08%	-2.88%	-2.25%	-33.23%	-23.48%	-18.29%	-1.88%	-1.33%	-1.04%	1.51%	3.23%	7.10%	1.29%	3.01%	4.73%	
(GJR)TGARCH (1,1)_GED	-2.97%	-2.73%	-2.42%	-22.58%	-20.73%	-18.43%	-1.59%	-1.46%	-1.30%	2.80%	3.44%	4.52%	2.37%	2.80%	3.44%	
EGARCH (1,1)_N	-4.59%	-3.25%	-2.53%	-12.19%	-8.62%	-6.72%	-3.86%	-2.73%	-2.13%	0.86%	2.80%	4.52%	0.43%	1.08%	3.87%	
EGARCH (1,1)_T	-3.87%	-2.73%	-2.13%	-34.22%	-24.19%	-18.84%	-2.10%	-1.48%	-1.16%	1.72%	4.09%	6.24%	0.65%	2.37%	5.59%	
EGARCH (1,1)_GED	-2.81%	-2.58%	-2.30%	-18.65%	-17.12%	-15.22%	-1.72%	-1.58%	-1.40%	3.01%	4.09%	5.59%	2.15%	2.80%	4.30%	
APARCH (1,1)_N	-4.47%	-3.16%	-2.46%	-16.24%	-11.48%	-8.95%	-3.89%	-2.75%	-2.15%	0.65%	2.37%	3.44%	0.43%	2.15%	4.95%	
APARCH (1,1)_T	-3.99%	-2.82%	-2.20%	-27.91%	-19.73%	-15.36%	-1.63%	-1.15%	-0.89%	1.51%	3.01%	6.24%	1.29%	3.01%	5.16%	
APARCH (1,1)_GED	-2.96%	-2.71%	-2.41%	-21.09%	-19.37%	-17.21%	-1.54%	-1.42%	-1.26%	2.80%	3.23%	4.30%	2.37%	3.01%	3.44%	
TARCH (1,1)_X_N	-4.53%	-3.20%	-2.50%	-16.65%	-11.78%	-9.18%	-3.53%	-2.50%	-1.95%	0.65%	1.51%	3.01%	0.43%	1.94%	4.52%	
TARCH (1,1)_X_T	-4.07%	-2.88%	-2.24%	-33.40%	-23.60%	-18.38%	-1.85%	-1.31%	-1.02%	1.51%	3.23%	6.88%	1.29%	3.01%	4.73%	
TARCH (1,1)_X_GED	-2.87%	-2.63%	-2.34%	-8.34%	-7.66%	-6.81%	-2.54%	-2.33%	-2.07%	2.37%	2.37%	4.09%	3.01%	3.66%	6.24%	
RISK METRICS	-2.34%	-3.62%	-2.56%	-6.81%	-8.30%	-5.87%	-1.49%	-1.05%	-0.82%	1.94%	3.87%	7.53%	2.37%	6.24%	9.89%	
HS(100) Long	-5.41%	-2.19%	-1.57%	-12.44%	-3.91%	-2.07%	-2.39%	-1.54%	-1.03%	1.29%	4.09%	10.75%	-	-	-	
HS(250) Long	-4.10%	-2.12%	-1.57%	-9.86%	-2.48%	-1.82%	-3.23%	-1.94%	-1.31%	0.86%	5.38%	9.68%	-	-	-	
HS(FS) Long	-4.04%	-2.15%	-1.59%	-4.24%	-2.21%	-1.62%	-3.92%	-2.11%	-1.56%	1.08%	4.95%	9.46%	-	-	-	
HS(100) Short	7.30%	4.11%	3.48%	5.72%	3.53%	3.04%	10.73%	4.62%	3.74%	-	-	-	0.00%	0.86%	2.37%	
HS(250) Short	4.03%	2.84%	2.10%	3.29%	2.46%	1.65%	4.62%	3.38%	2.51%	-	-	-	1.29%	5.38%	10.54%	
HS(FS) Short	6.21%	2.93%	1.86%	5.98%	2.83%	1.82%	6.46%	3.03%	1.93%	-	-	-	0.22%	5.38%	10.97%	

Table 16: Represents Value at Risk results for TC5 route's spot price returns. The first column presents the different model types that used to measure Value at Risk. The next nine columns present average, minimum and maximum VaR estimates at 1%, 5% and 10%, confidence levels, respectively. The last six columns present the HIT sequence as a percentage of the out-of-sample observations. HIT sequences are reported for both long and short positions.

6.2.2.2 FFA 1 Month

As per Table 6, TC5 1 Month's historical distribution is leptokurtic and skewed on the left side (Fischer Skewness Statistic equals -1.45). Figure 16 that include the QQ plots, is picturing the non-normality of the distribution with extreme returns being located on the left and right side of the normal distribution's diagram. Same is also confirmed by the JB test. As per Figure 20 the returns do not seem to have any serial autocorrelation, since all p-values equal to zero.

Table 20 suggests that both the parametric and the non-parametric models performed quite well for capturing the risk related to the long positions, with only exemption the 1-day Value at Risk estimates at 1% confidence level that have been calculated with parametric models that are assuming that the standard returns are following a Generalized Error Distribution. The models that passed most statistical tests for long positions are the GARCH(1, 1)_N, GARCH(1, 1)_T, IGARCH(1, 1)_N, TGARCH(1, 1)_N, TGARCH(1, 1)_T, EGARCH(1, 1)_N, APARCH(1, 1)_N, TGARCH(1, 1)_X_N, Risk Metrics, HS(100), HS(250) and HS(FS), while for short positions are the GARCH(1, 1)_N, IGARCH(1, 1)_N, IGARCH(1, 1)_T, TGARCH(1, 1)_N, TGARCH(1, 1)_N, EGARCH(1, 1)_N, APARCH(1, 1)_N, TGARCH(1, 1)_X_N and HS(250).

After comparing the models in terms of economic accuracy, the models that performed better for long positions are the GARCH(1, 1)_N, IGARCH(1, 1)_N, HS(100), HS(250) and HS(FS), while for short positions are the GARCH(1, 1)_N, IGARCH(1, 1)_N, HS(250) and HS(FS),

6.2.2.2.1 Value at Risk Statistics

TC5_1M															
Out of Sample Obs	Average VaR			Minimum VaR			Maximum VaR			Hit Sequence Long %			Hit Sequence Short %		
465	1%	5%	10%	1%	5%	10%	1%	5%	10%	1%	5%	10%	1%	5%	10%
Model															
GARCH (1,1)_N	-5.63%	-3.98%	-3.10%	-6.89%	-4.88%	-3.80%	-4.91%	-3.47%	-2.71%	1.08%	5.38%	8.17%	0.86%	4.52%	8.17%
GARCH (1,1)_T	-6.59%	-4.66%	-3.63%	-8.22%	-5.81%	-4.53%	-5.74%	-4.05%	-3.16%	0.65%	4.09%	6.45%	0.86%	1.94%	5.81%
GARCH (1,1)_GED	-4.12%	-3.78%	-3.36%	-9.20%	-8.44%	-7.50%	-3.31%	-3.03%	-2.70%	4.95%	5.81%	7.74%	3.66%	5.16%	7.10%
IGARCH (1,1)_N	-5.37%	-3.80%	-2.96%	-7.22%	-5.10%	-3.98%	-4.26%	-3.02%	-2.35%	1.94%	5.59%	8.39%	1.29%	5.81%	8.82%
IGARCH (1,1)_T	-5.48%	-3.87%	-3.02%	-6.88%	-4.86%	-3.79%	-4.67%	-3.30%	-2.57%	2.15%	5.38%	8.39%	1.29%	5.38%	8.60%
IGARCH (1,1)_GED	-4.01%	-3.68%	-3.28%	-4.97%	-4.56%	-4.05%	-3.44%	-3.16%	-2.81%	4.95%	6.02%	7.96%	4.52%	6.02%	7.53%
(GJR)TGARCH (1,1)_N	-5.69%	-4.02%	-3.13%	-7.36%	-5.21%	-4.06%	-4.77%	-3.37%	-2.63%	0.86%	5.38%	7.74%	0.86%	4.52%	8.17%
(GJR)TGARCH (1,1)_T	-6.81%	-4.81%	-3.75%	-8.99%	-6.35%	-4.95%	-5.71%	-4.04%	-3.15%	0.65%	3.44%	5.81%	0.86%	1.94%	5.81%
(GJR)TGARCH (1,1)_GED	-4.14%	-3.80%	-3.37%	-10.58%	-9.71%	-8.63%	-3.36%	-3.08%	-2.74%	4.73%	6.02%	7.74%	3.44%	5.16%	7.10%
EGARCH (1,1)_N	-6.05%	-4.28%	-3.33%	-9.14%	-6.46%	-5.04%	-4.15%	-2.94%	-2.29%	0.65%	4.09%	7.10%	0.86%	3.66%	7.53%
EGARCH (1,1)_T	-7.34%	-5.18%	-4.04%	-10.58%	-7.48%	-5.82%	-5.46%	-3.86%	-3.00%	0.65%	1.94%	5.38%	0.65%	1.51%	4.30%
EGARCH (1,1)_GED	-3.98%	-3.66%	-3.25%	-6.18%	-5.68%	-5.05%	-2.72%	-2.50%	-2.22%	5.38%	6.45%	7.96%	4.73%	6.02%	7.74%
APARCH (1,1)_N	-6.01%	-4.25%	-3.31%	-9.27%	-6.55%	-5.11%	-4.09%	-2.89%	-2.25%	0.65%	4.09%	7.31%	0.86%	3.66%	7.53%
APARCH (1,1)_T	-7.55%	-5.33%	-4.15%	-11.44%	-8.09%	-6.30%	-5.50%	-3.89%	-3.03%	0.43%	1.08%	4.52%	0.65%	1.08%	4.09%
APARCH (1,1)_GED	-3.87%	-3.55%	-3.16%	-12.56%	-11.53%	-10.25%	-2.97%	-2.73%	-2.42%	6.24%	7.31%	8.82%	4.73%	6.45%	8.17%
TARCH (1,1)_X_N	-5.37%	-3.80%	-2.96%	-7.24%	-5.12%	-3.99%	-3.53%	-2.50%	-1.95%	1.51%	6.45%	7.96%	0.86%	3.87%	8.17%
TARCH (1,1)_X_T	-6.55%	-4.63%	-3.61%	-8.56%	-6.05%	-4.71%	-5.25%	-3.71%	-2.89%	0.65%	3.01%	6.67%	0.65%	1.72%	6.24%
TARCH (1,1)_X_GED	-3.92%	-3.60%	-3.20%	-8.96%	-8.23%	-7.31%	-3.28%	-3.01%	-2.68%	5.38%	7.10%	8.17%	4.52%	6.67%	7.53%
RISK METRICS	-5.27%	-3.73%	-2.91%	-9.81%	-6.94%	-5.41%	-2.57%	-1.82%	-1.41%	1.94%	5.38%	8.17%	2.37%	6.67%	8.82%
HS(100) Long	-6.74%	-4.01%	-2.66%	-7.91%	-6.12%	-4.14%	-3.88%	-2.27%	-1.69%	0.43%	5.38%	9.03%	-	-	-
HS(250) Long	-7.17%	-4.04%	-2.24%	-8.08%	-5.17%	-3.44%	-6.06%	-3.77%	-2.00%	0.65%	5.59%	10.32%	-	-	-
HS(FS) Long	-9.34%	-4.45%	-2.70%	-9.66%	-4.61%	-2.82%	-8.08%	-4.33%	-2.63%	0.00%	4.30%	9.89%	-	-	-
HS(100) Short	11.64%	5.36%	4.29%	10.66%	4.47%	3.92%	15.08%	8.70%	5.08%	-	-	-	0.22%	1.72%	3.01%
HS(250) Short	7.32%	3.61%	2.44%	4.08%	3.31%	1.83%	10.64%	4.26%	3.20%	-	-	-	1.51%	6.24%	10.75%
HS(FS) Short	9.08%	4.45%	2.91%	8.83%	4.20%	2.87%	9.71%	4.74%	2.99%	-	-	-	0.65%	2.58%	8.60%
HS(100) Short	8.00%	4.46%	3.63%	8.00%	3.49%	2.05%	8.00%	5.06%	4.24%	-	-	-	0.22%	1.94%	3.66%
HS(250) Short	4.62%	2.33%	1.48%	4.20%	2.02%	1.15%	5.06%	3.28%	1.82%	-	-	-	1.29%	6.24%	10.97%
HS(FS) Short	5.06%	2.62%	1.73%	4.82%	2.56%	1.70%	5.17%	2.67%	1.79%	-	-	-	1.08%	4.95%	9.03%

Table 19: Represents Value at Risk results for TC5 route 1-Month front FFA price returns. The first column presents the different model types that used to measure Value at Risk. The next nine columns present average, minimum and maximum VaR estimates at 1%, 5% and 10%, confidence levels, respectively. The last six columns present the HIT sequence as a percentage of the out-of-sample observations. HIT sequences are reported for both long and short positions.

6.2.2.3 FFA 3 Months

As per Table 6 TC5 3 Months' historical distribution is leptokurtic and skewed on the left side (Fischer Skewness Statistic equals -1.15). Examining the QQ plots on the Figure 16, it can be seen that TC5 FFA 3 months front contacts have experienced some extreme negative returns. According to Figure 20 the returns do not seem to have any serial autocorrelation, since all p-values equal to zero. JB test clearly suggests the non-normality of the distribution.

As per Tables 22 and 23 the models that resulted adequate scores close to or below the critical values of the statistical tests, are the GARCH(1, 1)_N, TGARCH(1, 1)_N, EGARCH(1, 1)_N, HS(100), HS(250) and HS(FS) for long positions, and the GARCH(1, 1)_N, HS(250) and HS(FS) for short positions. After filtering for minimum QLF scores, the best performers are the HS(250) and HS(FS) for both long and short positions.

6.2.2.3.1 Value at Risk Statistics

TC5_3M																
Out of Sample Obs	Average VaR			Minimum VaR			Maximum VaR			Hit Sequence Long %			Hit Sequence Short %			
	465	1%	5%	10%	1%	5%	10%	1%	5%	10%	1%	5%	10%	1%	5%	10%
Model																
GARCH (1,1)_N	-4.12%	-2.91%	-2.27%	-9.88%	-6.99%	-5.45%	-2.51%	-1.78%	-1.39%	1.08%	3.66%	6.67%	2.58%	5.38%	6.67%	
GARCH (1,1)_T	-7.66%	-5.42%	-4.22%	-11.40%	-8.06%	-6.27%	-4.51%	-3.19%	-2.48%	0.00%	0.65%	0.86%	0.00%	1.29%	2.15%	
GARCH (1,1)_GED	-2.29%	-2.11%	-1.87%	-6.03%	-5.53%	-4.92%	-1.54%	-1.41%	-1.26%	6.67%	7.74%	8.60%	6.67%	6.88%	7.96%	
IGARCH (1,1)_N	-3.29%	-2.33%	-1.82%	-4.27%	-3.02%	-2.35%	-2.62%	-1.85%	-1.44%	2.37%	6.02%	9.03%	3.23%	6.02%	8.60%	
IGARCH (1,1)_T	-3.28%	-2.32%	-1.81%	-4.42%	-3.12%	-2.43%	-2.40%	-1.69%	-1.32%	2.58%	6.24%	9.25%	3.44%	6.24%	8.82%	
IGARCH (1,1)_GED	-2.68%	-2.46%	-2.19%	-2.73%	-2.51%	-2.23%	-2.62%	-2.41%	-2.14%	4.52%	5.59%	6.67%	4.95%	5.16%	7.53%	
(GJR)TGARCH (1,1)_N	-4.11%	-2.91%	-2.27%	-10.04%	-7.10%	-5.54%	-2.55%	-1.80%	-1.41%	1.08%	3.44%	6.45%	2.58%	5.16%	6.88%	
(GJR)TGARCH (1,1)_T	-12.02%	-8.50%	-6.62%	-18.53%	-13.09%	-10.20%	-7.75%	-5.48%	-4.27%	0.00%	0.00%	0.00%	0.00%	0.00%	0.22%	
(GJR)TGARCH (1,1)_GED	-2.55%	-2.34%	-2.08%	-5.43%	-4.99%	-4.43%	-1.97%	-1.81%	-1.61%	4.95%	5.59%	6.88%	5.81%	6.24%	6.88%	
EGARCH (1,1)_N	-4.05%	-2.86%	-2.23%	-8.42%	-5.96%	-4.64%	-2.40%	-1.69%	-1.32%	1.08%	4.30%	6.67%	2.80%	4.52%	6.88%	
EGARCH (1,1)_T	-11.60%	-8.20%	-6.39%	-34.09%	-24.10%	-18.77%	-6.81%	-4.82%	-3.75%	0.00%	0.00%	0.00%	0.00%	0.00%	0.22%	
EGARCH (1,1)_GED	-2.52%	-2.32%	-2.06%	-5.25%	-4.82%	-4.28%	-2.03%	-1.86%	-1.66%	5.38%	5.59%	6.88%	5.38%	6.45%	7.31%	
APARCH (1,1)_N	-3.96%	-2.80%	-2.18%	-8.07%	-5.70%	-4.45%	-2.14%	-1.52%	-1.18%	1.08%	4.30%	6.88%	2.58%	4.95%	7.31%	
APARCH (1,1)_T	-6.96%	-4.92%	-3.83%	-15.87%	-11.22%	-8.74%	-2.54%	-1.79%	-1.40%	0.43%	0.86%	2.37%	0.43%	1.51%	3.44%	
APARCH (1,1)_GED	-2.37%	-2.18%	-1.94%	-5.81%	-5.33%	-4.74%	-1.20%	-1.10%	-0.98%	6.24%	7.31%	8.39%	6.45%	7.10%	8.39%	
TARCH (1,1)_X_N	-4.11%	-2.91%	-2.27%	-10.03%	-7.09%	-5.53%	-2.56%	-1.81%	-1.41%	1.08%	3.23%	6.45%	2.58%	5.16%	6.88%	
TARCH (1,1)_X_T	-11.56%	-8.17%	-6.36%	-17.27%	-12.21%	-9.51%	-7.42%	-5.25%	-4.09%	0.00%	0.22%	0.00%	0.00%	0.43%		
TARCH (1,1)_X_GED	-2.59%	-2.38%	-2.11%	-4.98%	-4.57%	-4.06%	-2.00%	-1.83%	-1.63%	4.95%	5.59%	6.67%	5.81%	6.02%	6.88%	
RISK METRICS	-3.31%	-2.34%	-1.83%	-6.49%	-4.59%	-3.57%	-1.65%	-1.16%	-0.91%	2.15%	5.38%	10.11%	3.66%	6.24%	9.89%	
HS(100) Long	-4.16%	-2.43%	-1.62%	-5.81%	-3.48%	-2.28%	-1.89%	-1.34%	-0.95%	1.94%	5.59%	10.97%	-	-	-	
HS(250) Long	-4.54%	-2.25%	-1.51%	-5.01%	-2.79%	-1.95%	-4.14%	-1.87%	-0.96%	0.43%	6.24%	11.40%	-	-	-	
HS(FS) Long	-5.18%	-2.67%	-1.76%	-5.42%	-2.82%	-1.79%	-5.00%	-2.56%	-1.74%	0.43%	4.73%	9.46%	-	-	-	
HS(100) Short	8.00%	4.46%	3.63%	8.00%	3.49%	2.05%	8.00%	5.06%	4.24%	-	-	-	0.22%	1.94%	3.66%	
HS(250) Short	4.62%	2.33%	1.48%	4.20%	2.02%	1.15%	5.06%	3.28%	1.82%	-	-	-	1.29%	6.24%	10.97%	
HS(FS) Short	5.06%	2.62%	1.73%	4.82%	2.56%	1.70%	5.17%	2.67%	1.79%	-	-	-	1.08%	4.95%	9.03%	

Table 22: Represents Value at Risk results for TC5 route 3-Months front FFA price returns. The first column presents the different model types that used to measure Value at Risk. The next nine columns present average, minimum and maximum VaR estimates at 1%, 5% and 10%, confidence levels, respectively. The last six columns present the HIT sequence as a percentage of the out-of-sample observations. HIT sequences are reported for both long and short positions.

6.2.3 TD3

6.2.3.1 Spot

As per Table 6, TD3 Spot's historical distribution is experiencing excess kurtosis and positive skewness with the relevant tests having resulted values of 14.28 and 0.42, respectively. Figure 16 that includes the QQ plots clearly depicts the positive skewness with extreme returns to be located on the right side of the normal distribution's diagram. Figure 20 that includes the autocorrelations, rejects any suspicion of serious autocorrelation between the returns with all p-values equal to zero. The JB test also suggests the non-normality of the distribution. These results are congruent with findings from earlier periods by Abouarghoub (2008) and Angelidis and Skiadopoulos (2008), who applied similar methodologies on freight indexes and spot price returns.

Referring to Tables 26 and 27, it can be seen that no model passed all statistical tests, however the GARCH(1, 1)_N, TGARCH_N, EGARCH(1, 1)_N, APARCH(1, 1)_N, HS(100), HS(250) and HS(FS) resulted satisfying results overall for both long and short positions. It can be justified from the results that even though the aforementioned models passed the unconditional coverage test almost at all levels, they failed at the independence test, thus also failing to the joint test. After filtering for statistically significant coefficients the models that models in the shortlist are GARCH(1, 1)_N and EGARCH(1, 1)_N.

Testing now for economic accuracy, by examining the QLF scores, the models that should be used for TD3-S' risk management are GARCH(1, 1)_N, HS(100), HS(250) and HS(FS), for both long and short positions.

6.2.3.1 Value at Risk Statistics

Out of Sample Obs	TD3_S														
	Average VaR			Minimum VaR			Maximum VaR			Hit Sequence Long %			Hit Sequence Short %		
	526	1%	5%	10%	1%	5%	10%	1%	5%	10%	1%	5%	10%	1%	5%
Model															
GARCH (1,1)_N	-8.96%	-6.34%	-4.94%	-41.18%	-29.12%	-22.70%	-4.88%	-3.45%	-2.69%	1.14%	3.80%	6.27%	1.33%	4.37%	7.03%
GARCH (1,1)_T	-338.98%	-239.57%	-186.59%	-2535.35%	-1791.84%	-1395.59%	-131.88%	-93.21%	-72.59%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
GARCH (1,1)_GED	-6.90%	-6.30%	-5.60%	-45.09%	-41.21%	-36.63%	-2.87%	-2.62%	-2.33%	3.42%	3.99%	5.89%	3.61%	3.99%	5.51%
IGARCH (1,1)_N	-8.02%	-5.67%	-4.42%	-15.53%	-10.98%	-8.56%	-3.72%	-2.63%	-2.05%	2.09%	3.99%	6.84%	2.66%	5.89%	8.75%
IGARCH (1,1)_T	-7.60%	-5.37%	-4.18%	-22.54%	-15.93%	-12.41%	-2.08%	-1.47%	-1.14%	2.28%	5.32%	7.41%	3.42%	7.41%	10.27%
IGARCH (1,1)_GED	-5.67%	-5.18%	-4.61%	-14.93%	-13.62%	-12.10%	-1.95%	-1.78%	-1.58%	4.18%	5.13%	6.27%	6.08%	7.79%	9.70%
(GJR)TGARCH (1,1)_N	-8.99%	-6.36%	-4.95%	-42.44%	-30.02%	-23.39%	-4.86%	-3.43%	-2.68%	1.14%	4.18%	6.46%	1.33%	4.18%	7.03%
(GJR)TGARCH (1,1)_T	-324.49%	-229.33%	-178.62%	-2376.37%	-1679.48%	-1308.07%	-126.09%	-89.11%	-69.41%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
(GJR)TGARCH (1,1)_GED	-6.88%	-6.29%	-5.59%	-44.25%	-40.44%	-35.95%	-2.88%	-2.63%	-2.34%	3.42%	3.99%	5.70%	3.61%	4.18%	5.70%
EGARCH (1,1)_N	-8.93%	-6.31%	-4.92%	-59.01%	-41.73%	-32.52%	-4.04%	-2.86%	-2.23%	0.95%	3.99%	6.27%	1.90%	3.99%	6.84%
EGARCH (1,1)_T	-21.57%	-15.24%	-11.87%	-332.53%	-235.01%	-183.04%	-8.61%	-6.08%	-4.74%	0.00%	0.00%	0.19%	0.19%	0.57%	0.95%
EGARCH (1,1)_GED	-6.46%	-5.90%	-5.24%	-76.98%	-70.36%	-62.54%	-2.72%	-2.47%	-2.20%	3.61%	4.37%	6.08%	3.99%	5.32%	6.08%
APARCH (1,1)_N	-8.95%	-6.33%	-4.93%	-37.13%	-26.26%	-20.46%	-4.51%	-3.19%	-2.49%	0.76%	3.80%	6.27%	1.52%	3.99%	7.41%
APARCH (1,1)_T	-48.87%	-34.54%	-26.90%	-264.53%	-186.95%	-145.61%	-14.77%	-10.44%	-8.13%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
APARCH (1,1)_GED	-6.69%	-6.11%	-5.43%	-32.82%	-29.97%	-26.64%	-2.28%	-2.09%	-1.85%	3.23%	3.80%	5.51%	4.37%	4.94%	5.13%
TARCH (1,1)_X_N	-9.21%	-6.52%	-5.08%	-47.23%	-33.40%	-26.03%	-4.15%	-2.93%	-2.29%	0.95%	3.99%	6.46%	1.33%	3.80%	6.84%
TARCH (1,1)_X_T	-301.49%	-213.08%	-165.96%	-2210.88%	-1562.52%	-1216.98%	-103.54%	-73.18%	-56.99%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
TARCH (1,1)_X_GED	-6.90%	-6.30%	-5.60%	-44.59%	-40.75%	-36.22%	-2.58%	-2.35%	-2.09%	3.42%	4.56%	5.32%	3.23%	4.18%	5.89%
RISK METRICS	-7.87%	-5.57%	-4.34%	-18.33%	-12.97%	-10.11%	-2.81%	-1.99%	-1.55%	2.28%	4.18%	7.22%	3.04%	6.84%	9.89%
HS(100) Long	-9.74%	-5.51%	-3.48%	-17.17%	-8.55%	-5.42%	-2.98%	-1.03%	-0.77%	1.90%	5.89%	11.22%	-	-	-
HS(250) Long	-9.53%	-5.05%	-3.31%	-10.00%	-6.53%	-4.11%	-7.48%	-3.51%	-2.42%	1.33%	5.51%	10.84%	-	-	-
HS(FS) Long	-11.02%	-6.01%	-3.68%	-11.16%	-6.16%	-3.82%	-10.84%	-5.90%	-3.59%	0.19%	4.37%	9.32%	-	-	-
HS(100) Short	15.24%	6.42%	3.88%	7.58%	2.90%	1.82%	23.92%	11.09%	6.29%	-	-	-	1.33%	5.13%	10.46%
HS(250) Short	11.14%	5.63%	3.31%	8.52%	3.84%	2.17%	12.98%	6.95%	4.72%	-	-	-	1.71%	5.13%	11.60%
HS(FS) Short	13.88%	6.77%	3.86%	13.48%	6.56%	3.78%	14.02%	7.01%	3.99%	-	-	-	0.57%	3.80%	10.27%

Table 25: Represents Value at Risk results for TD3 route spot price returns. The first column presents the different model types that used to measure Value at Risk. The next nine columns present average, minimum and maximum VaR estimates at 1%, 5% and 10%, confidence levels, respectively. The last six columns present the HIT sequence as a percentage of the out-of-sample observations. HIT sequences are reported for both long and short positions.

6.2.3.2 FFA 1 Month

As per Table 6 TD3 1 Month's historical distribution is leptokurtic and slightly skewed on the left side (Fischer Skewness Statistic equals -0.30). However, as per Figure 16 this skewness cannot be clearly illustrated on the QQ plots due to its insignificance. Figure 20 that includes the autocorrelations rejects any suspicion of serious autocorrelation between the returns with all p-values equal to zero. The JB test supports the non-normality of the distribution.

From Tables 29 and 30 it can be seen that the parametric models that passed most statistical tests are the GARCH(1, 1)_N, IGARCH(1, 1)_N, TGARCH(1, 1)_N, TGARCH(1, 1)_T and Risk Metrics for both long and short positions. All mentioned GARCH-family models presented statistically significant coefficients. On the other hand all non-parametric models passed almost all statistical tests.

Comparing now the models with each other in terms of economic accuracy, the models that are suggested for TD3_1M' risk management for both long and short positions are GARCH(1, 1)_N, HS(100), HS(250) and HS(FS).

6.2.3.2.1 Value at Risk Statistics

Out of Sample Obs	TD3_1M															
	526	Average VaR			Minimum VaR			Maximum VaR			Hit Sequence Long %			Hit Sequence Short %		
		1%	5%	10%	1%	5%	10%	1%	5%	10%	1%	5%	10%	1%	5%	10%
Model																
GARCH (1,1)_N	-11.28%	-7.97%	-6.21%	-67.15%	-47.49%	-37.01%	-6.52%	-4.61%	-3.60%	1.33%	3.04%	5.70%	1.90%	4.56%	6.08%	
GARCH (1,1)_T	-16.93%	-11.97%	-9.32%	-74.67%	-52.77%	-41.10%	-9.47%	-6.70%	-5.21%	0.57%	0.95%	1.71%	0.76%	1.90%	2.28%	
GARCH (1,1)_GED	-7.21%	-6.59%	-5.85%	-53.63%	-49.07%	-43.62%	-5.13%	-4.68%	-4.15%	3.80%	4.37%	5.70%	4.37%	5.51%	6.65%	
IGARCH (1,1)_N	-10.14%	-7.17%	-5.59%	-51.07%	-36.12%	-28.15%	-4.13%	-2.92%	-2.28%	1.71%	4.56%	7.98%	2.66%	5.51%	8.17%	
IGARCH (1,1)_T	-10.84%	-7.66%	-5.97%	-34.89%	-24.66%	-19.21%	-5.13%	-3.62%	-2.82%	1.52%	3.42%	6.08%	2.28%	4.37%	7.03%	
IGARCH (1,1)_GED	-8.08%	-7.38%	-6.56%	-22.07%	-20.19%	-17.95%	-3.98%	-3.63%	-3.23%	2.85%	3.61%	4.94%	3.42%	4.37%	5.70%	
(GJR)TGARCH (1,1)_N	-11.20%	-7.92%	-6.18%	-69.11%	-48.87%	-38.09%	-6.46%	-4.57%	-3.56%	1.14%	3.04%	5.70%	1.71%	4.18%	6.27%	
(GJR)TGARCH (1,1)_T	-17.00%	-12.01%	-9.36%	-71.83%	-50.76%	-39.54%	-9.37%	-6.62%	-5.16%	0.57%	1.14%	2.09%	0.76%	1.90%	2.66%	
(GJR)TGARCH (1,1)_GED	-7.34%	-6.71%	-5.96%	-54.15%	-49.54%	-44.04%	-4.54%	-4.14%	-3.68%	3.99%	4.18%	6.27%	4.75%	5.70%	6.46%	
EGARCH (1,1)_N	-10.68%	-7.56%	-5.89%	-57.05%	-40.34%	-31.44%	-5.84%	-4.13%	-3.22%	1.14%	3.04%	5.32%	1.71%	4.37%	6.08%	
EGARCH (1,1)_T	-13.74%	-9.71%	-7.56%	-41.16%	-29.09%	-22.66%	-7.25%	-5.12%	-3.99%	0.57%	1.52%	3.80%	1.33%	2.47%	3.61%	
EGARCH (1,1)_GED	-7.01%	-6.40%	-5.69%	-8.17%	-7.48%	-6.65%	-4.28%	-3.92%	-3.48%	2.85%	3.42%	4.94%	3.23%	3.42%	5.13%	
APARCH (1,1)_N	-10.90%	-7.71%	-6.01%	-61.20%	-43.28%	-33.73%	-6.28%	-4.44%	-3.46%	0.95%	3.23%	5.70%	1.90%	4.56%	6.46%	
APARCH (1,1)_T	-13.23%	-9.35%	-7.28%	-28.55%	-20.18%	-15.72%	-7.10%	-5.02%	-3.91%	0.57%	1.90%	3.61%	1.33%	2.66%	3.99%	
APARCH (1,1)_GED	-6.63%	-6.05%	-5.38%	-21.50%	-19.68%	-17.49%	-3.37%	-3.07%	-2.72%	4.56%	4.94%	6.65%	5.32%	6.27%	7.22%	
TARCH (1,1)_X_N	-11.30%	-7.99%	-6.23%	-71.31%	-50.43%	-39.30%	-5.99%	-4.23%	-3.30%	1.14%	3.04%	5.70%	1.71%	3.42%	6.08%	
TARCH (1,1)_X_T	-17.14%	-12.11%	-9.43%	-69.88%	-49.39%	-38.46%	-9.79%	-6.92%	-5.39%	0.57%	1.14%	2.28%	0.76%	1.71%	2.66%	
TARCH (1,1)_X_GED	-6.92%	-6.32%	-5.62%	-44.84%	-41.03%	-36.47%	-5.31%	-4.83%	-4.30%	3.23%	4.18%	5.70%	3.80%	4.37%	7.03%	
RISK METRICS	-10.20%	-7.22%	-5.62%	-49.24%	-34.82%	-27.14%	-4.22%	-2.98%	-2.33%	1.71%	4.37%	7.79%	2.66%	5.51%	7.79%	
HS(100) Long	-22.36%	-5.78%	-3.91%	-61.12%	-9.53%	-5.30%	-4.76%	-2.84%	-2.07%	1.14%	6.46%	9.89%	-	-	-	
HS(250) Long	-14.60%	-5.22%	-3.43%	-25.24%	-6.22%	-4.55%	-8.66%	-3.92%	-2.25%	0.95%	5.51%	12.17%	-	-	-	
HS(FS) Long	-17.69%	-7.03%	-4.56%	-18.10%	-7.41%	-4.68%	-17.17%	-6.78%	-4.47%	0.38%	3.04%	7.41%	-	-	-	
HS(100) Short	22.07%	6.07%	4.03%	7.23%	4.94%	2.47%	61.12%	8.89%	5.51%	-	-	-	1.33%	5.32%	11.03%	
HS(250) Short	11.71%	5.37%	3.92%	8.11%	4.32%	2.60%	15.59%	6.06%	4.80%	-	-	-	1.71%	6.08%	11.41%	
HS(FS) Short	14.41%	7.27%	5.06%	14.02%	7.08%	4.98%	14.54%	7.41%	5.24%	-	-	-	0.95%	3.23%	7.22%	

Table 28: Represents Value at Risk results for TD3 route 1 month price returns. The first column presents the different model types that used to measure Value at Risk. The next nine columns present average, minimum and maximum VaR estimates at 1%, 5% and 10%, confidence levels, respectively. The last six columns present the HIT sequences as a percentage of the out-of-sample observations. HIT sequences are reported for both long and short positions.

6.2.3.3 FFA 3 Months

As per Table 6 TD3 3 Months' historical distribution is leptokurtic and slightly skewed at the left side (Fischer Skewness Statistic equals -0.43). Figure 20 that includes the autocorrelations rejects any suspicion of serious autocorrelation between the returns with all p-values equal to zero. The JB test supports the non-normality of the distribution.

The augmented TGARCH that incorporates the spot-3 months slop of returns with t-distribution assumption could not be estimated for the TD3 3 months price returns.

As per Tables 32 and 33 it can be seen that no parametric model performed well at the statistical tests for long positions at VaR1%, where zero hypothesis of the unconditional test has been rejected for all models. Same results are presented also for short positions, with only a few parametric models passing the statistical tests at VaR5% and VaR10%. On the other hand, both HS(100) and HS(250) passed all the tests at all levels for both long and short positions.

By comparing the models in terms of economic accuracy, the non-parametric ones should be preferred for TD3_3M's risk management purposes.

6.2.3.3.1 Value at Risk Statistics

Out of Sample Obs	TD3_3M														
	Average VaR			Minimum VaR			Maximum VaR			Hit Sequence Long %			Hit Sequence Short %		
	526	1%	5%	10%	1%	5%	10%	1%	5%	10%	1%	5%	10%	1%	5%
Model															
GARCH (1,1)_N	-5.48%	-3.87%	-3.02%	-15.74%	-11.13%	-8.67%	-3.11%	-2.20%	-1.72%	2.28%	3.23%	6.46%	1.90%	4.56%	6.65%
GARCH (1,1)_T	-5.84%	-4.12%	-3.21%	-15.19%	-10.74%	-8.36%	-2.61%	-1.85%	-1.44%	1.90%	3.04%	5.32%	1.90%	3.99%	6.08%
GARCH (1,1)_GED	-4.02%	-3.68%	-3.27%	-13.45%	-12.32%	-10.95%	-3.04%	-2.77%	-2.46%	3.42%	4.56%	5.70%	3.80%	4.56%	5.70%
IGARCH (1,1)_N	-4.60%	-3.25%	-2.53%	-8.14%	-5.76%	-4.49%	-2.86%	-2.02%	-1.58%	2.85%	3.99%	7.41%	2.66%	6.46%	8.94%
IGARCH (1,1)_T	-4.65%	-3.29%	-2.56%	-8.83%	-6.24%	-4.86%	-2.71%	-1.92%	-1.49%	2.85%	3.80%	7.79%	2.66%	6.65%	8.94%
IGARCH (1,1)_GED	-3.33%	-3.04%	-2.71%	-5.54%	-5.08%	-4.51%	-2.18%	-1.99%	-1.77%	3.99%	4.94%	6.84%	6.08%	7.79%	8.56%
(GJR)TGARCH (1,1)_N	-5.44%	-3.85%	-3.00%	-14.73%	-10.42%	-8.12%	-3.04%	-2.15%	-1.68%	2.09%	3.42%	6.65%	1.90%	4.56%	6.84%
(GJR)TGARCH (1,1)_T	-17.59%	-12.43%	-9.68%	-41.75%	-29.51%	-22.98%	-7.61%	-5.38%	-4.19%	0.00%	0.19%	0.19%	0.00%	0.19%	0.57%
(GJR)TGARCH (1,1)_GED	-4.05%	-3.70%	-3.29%	-13.64%	-12.49%	-11.11%	-3.02%	-2.76%	-2.45%	3.42%	4.56%	5.70%	3.99%	4.75%	5.70%
EGARCH (1,1)_N	-5.37%	-3.79%	-2.96%	-11.68%	-8.26%	-6.44%	-2.55%	-1.80%	-1.40%	2.28%	3.23%	6.08%	1.90%	4.18%	7.03%
EGARCH (1,1)_T	-14.68%	-10.37%	-8.08%	-37.53%	-26.52%	-20.66%	-5.98%	-4.22%	-3.29%	0.00%	0.19%	0.19%	0.00%	0.38%	0.95%
EGARCH (1,1)_GED	-4.17%	-3.81%	-3.39%	-12.53%	-11.48%	-10.20%	-3.18%	-2.90%	-2.58%	3.04%	3.80%	4.94%	3.42%	4.37%	5.51%
APARCH (1,1)_N	-5.36%	-3.79%	-2.95%	-11.84%	-8.37%	-6.53%	-2.65%	-1.87%	-1.46%	2.28%	3.23%	6.46%	1.90%	4.37%	7.03%
APARCH (1,1)_T	-13.85%	-9.79%	-7.62%	-34.77%	-24.57%	-19.14%	-5.69%	-4.02%	-3.13%	0.00%	0.19%	0.76%	0.19%	0.38%	0.95%
APARCH (1,1)_GED	-3.77%	-3.44%	-3.06%	-13.84%	-12.68%	-11.27%	-2.59%	-2.36%	-2.10%	4.18%	5.13%	6.65%	4.75%	5.13%	6.84%
TARCH (1,1)_X_N	-5.45%	-3.86%	-3.01%	-14.72%	-10.41%	-8.11%	-3.01%	-2.13%	-1.66%	2.09%	3.42%	6.65%	1.90%	4.56%	6.84%
TARCH (1,1)_X_T	-3.87%	-3.54%	-3.15%	-9.91%	-9.08%	-8.07%	-2.55%	-2.33%	-2.07%	3.42%	4.37%	5.70%	4.18%	5.13%	6.27%
RISK METRICS	-4.72%	-3.33%	-2.60%	-13.05%	-9.23%	-7.20%	-1.71%	-1.21%	-0.94%	2.85%	4.75%	7.79%	3.04%	5.70%	8.75%
HS(100) Long	-6.45%	-3.26%	-2.16%	-9.91%	-5.65%	-3.08%	-3.08%	-1.36%	-1.22%	1.33%	6.08%	10.27%	-	-	-
HS(250) Long	-6.47%	-2.96%	-1.93%	-7.67%	-4.08%	-2.82%	-4.88%	-2.53%	-1.32%	1.14%	6.27%	12.17%	-	-	-
HS(FS) Long	-9.03%	-4.51%	-2.92%	-9.36%	-4.88%	-3.06%	-8.43%	-4.31%	-2.82%	0.19%	2.66%	6.65%	-	-	-
HS(100) Short	7.96%	3.47%	2.38%	3.67%	2.38%	1.32%	16.99%	7.20%	3.45%	-	-	-	1.33%	5.70%	10.27%
HS(250) Short	5.94%	3.17%	2.07%	4.83%	2.47%	1.36%	8.62%	3.67%	2.74%	-	-	-	1.33%	6.27%	11.41%
HS(FS) Short	9.02%	4.50%	2.83%	8.59%	4.34%	2.72%	9.18%	4.65%	2.93%	-	-	-	0.57%	3.04%	7.98%

Table 31: Represents Value at Risk results for TD3 route 3 months price returns. The first column presents the different model types that used to measure Value at Risk. The next nine columns present average, minimum and maximum VaR estimates at 1%, 5% and 10%, confidence levels, respectively. The last six columns present the HIT sequence as a percentage of the out-of-sample observations. HIT sequences are reported for both long and short positions.

6.2.4 TD7

6.2.4.1 Spot

As per Table 6, TD7 spot's historical distribution is leptokurtic and skewed at the right side (Fischer Skewness Statistic equals 0.66). Figure 16 that includes the QQ plots, gives an illustration of the positive skewness, since it presents some extreme returns on the right side of normal distribution's diagram. Figure 20 that includes the autocorrelations rejects any suspicion of serious autocorrelation between the returns with all p-values equal to zero. The JB test supports the non-normality of the distribution. These results are congruent with findings from earlier period by Abouarghoub (2008).

Tables 35 and 36, clearly depicts the parametric models' incapacity of capturing risk at VaR5% and VaR10% for both long and short positions, since they resulted over conservative results. However, their performance is satisfying at VaR1% for both long and short positions. Both HS(250) and HS(FS) presented good results for both long and short positions.

Comparing the models by their resulted QLF scores, it is clear that the non-parametric models performed better overall for both long and short positions, at all confidence levels.

6.2.4.1 Value at Risk Statistics

TD7_S															
Out of Sample Obs	Average VaR			Minimum VaR			Maximum VaR			Hit Sequence Long %			Hit Sequence Short %		
	465	1%	5%	10%	1%	5%	10%	1%	5%	10%	1%	5%	10%	1%	5%
Model															
GARCH (1,1)_N	-16.57%	-11.72%	-9.13%	-163.99%	-115.97%	-90.38%	-1.44%	-1.02%	-0.80%	1.51%	2.37%	3.44%	1.51%	2.37%	3.01%
GARCH (1,1)_T	-20.40%	-14.42%	-11.23%	-206.84%	-146.18%	-113.86%	-0.18%	-0.13%	-0.10%	1.51%	2.15%	2.37%	1.51%	2.15%	2.58%
GARCH (1,1)_GED	-7.57%	-6.95%	-6.17%	-63.24%	-58.08%	-51.62%	-1.10%	-1.01%	-0.90%	3.01%	3.44%	4.09%	2.80%	3.23%	3.66%
IGARCH (1,1)_N	-11.18%	-7.91%	-6.16%	-24.59%	-17.39%	-13.55%	-3.00%	-2.12%	-1.65%	1.08%	1.72%	2.58%	1.08%	2.15%	2.58%
IGARCH (1,1)_T	-8.73%	-6.17%	-4.81%	-57.37%	-40.55%	-31.58%	-0.39%	-0.28%	-0.22%	2.58%	3.66%	4.30%	2.80%	3.44%	4.73%
IGARCH (1,1)_GED	-8.31%	-7.62%	-6.78%	-16.62%	-15.25%	-13.55%	-2.43%	-2.23%	-1.98%	1.51%	1.94%	2.37%	1.94%	1.94%	2.37%
(GJR)TGARCH (1,1)_N	-13.34%	-9.44%	-7.35%	-87.54%	-61.91%	-48.25%	-2.19%	-1.55%	-1.21%	1.29%	2.37%	3.87%	0.86%	1.29%	2.37%
(GJR)TGARCH (1,1)_T	-17.11%	-12.09%	-9.42%	-172.31%	-121.78%	-94.85%	-0.33%	-0.23%	-0.18%	1.51%	2.15%	2.58%	1.51%	2.37%	2.58%
(GJR)TGARCH (1,1)_G	-8.70%	-7.98%	-7.10%	-95.15%	-87.38%	-77.67%	-1.34%	-1.23%	-1.09%	3.44%	3.87%	3.87%	2.80%	3.01%	3.44%
EGARCH (1,1)_N	-12.07%	-8.53%	-6.65%	-54.26%	-38.37%	-29.91%	-2.47%	-1.75%	-1.36%	1.51%	2.58%	3.44%	1.08%	1.51%	1.94%
EGARCH (1,1)_T	-124.49%	-87.98%	-68.53%	-27978.17%	-19773.32%	-15400.61%	-3.79%	-2.68%	-2.08%	0.22%	1.08%	1.94%	0.22%	0.86%	1.29%
EGARCH (1,1)_GED	-10.01%	-9.19%	-8.17%	-478.59%	-439.31%	-390.50%	-1.31%	-1.20%	-1.07%	3.23%	3.44%	4.09%	2.37%	2.80%	3.66%
APARCH (1,1)_N	-11.43%	-8.08%	-6.30%	-46.64%	-32.99%	-25.71%	-2.10%	-1.48%	-1.16%	1.51%	2.37%	3.87%	1.08%	1.51%	2.15%
APARCH (1,1)_T	-33.60%	-23.75%	-18.50%	-320.68%	-226.64%	-176.52%	-0.62%	-0.44%	-0.34%	0.65%	0.86%	1.72%	0.43%	0.86%	1.29%
APARCH (1,1)_GED	-8.17%	-7.50%	-6.67%	-65.35%	-60.01%	-53.34%	-0.36%	-0.33%	-0.29%	3.23%	3.66%	3.87%	2.80%	2.80%	3.23%
TARCH (1,1)_X_N	-12.00%	-8.48%	-6.61%	-43.35%	-30.66%	-23.89%	-3.71%	-2.63%	-2.05%	0.86%	1.51%	2.58%	0.43%	1.08%	1.72%
TARCH (1,1)_X_T	-11.13%	-7.87%	-6.13%	-38.94%	-27.52%	-21.43%	-3.54%	-2.50%	-1.95%	1.08%	2.15%	2.80%	0.43%	1.08%	1.94%
TARCH (1,1)_X_GED	-7.41%	-6.80%	-6.05%	-50.29%	-46.18%	-41.05%	-1.95%	-1.79%	-1.59%	2.15%	2.37%	3.23%	1.08%	1.08%	1.72%
RISK METRICS	-6.36%	-4.50%	-3.51%	-28.83%	-20.39%	-15.89%	-2.11%	-1.50%	-1.17%	2.80%	3.87%	4.52%	2.37%	4.09%	4.95%
HS(100) Long	-15.84%	-2.88%	-0.62%	-36.10%	-7.41%	-2.18%	-2.82%	-0.86%	0.00%	1.08%	4.95%	8.39%	-	-	-
HS(250) Long	-10.01%	-2.59%	-0.71%	-12.52%	-3.54%	-1.10%	-4.26%	-0.93%	0.00%	1.51%	4.73%	8.60%	-	-	-
HS(FS) Long	-9.24%	-3.76%	-2.16%	-9.65%	-3.82%	-2.29%	-8.79%	-3.64%	-2.06%	1.72%	3.87%	4.95%	-	-	-
HS(100) Short	20.73%	7.88%	4.35%	14.31%	2.99%	0.95%	36.10%	10.79%	7.47%	-	-	-	0.00%	1.72%	3.01%
HS(250) Short	9.35%	2.45%	0.97%	3.18%	1.71%	0.00%	10.92%	3.35%	1.37%	-	-	-	1.51%	5.59%	9.68%
HS(FS) Short	9.10%	3.81%	2.24%	8.75%	3.70%	2.17%	9.61%	4.04%	2.50%	-	-	-	1.29%	3.44%	6.02%

Table 34: Represents Value at Risk results for TD7 route spot price returns. The first column presents the different model types that used to measure Value at Risk. The next nine columns present average, minimum and maximum VaR estimates at 1%, 5% and 10%, confidence levels, respectively. The last six columns present the HIT sequence as a percentage of the out-of-sample observations. HIT sequences are reported for both long and short positions.

6.2.4.2 FFA 1 Month

As per Table 6, TD7 1 Month's historical distribution is leptokurtic and slightly skewed at the left side (Fischer Skewness Statistic equals -0.48). Figure 16 which includes the QQ plots, clearly depicts the distribution's non-normality. Same is supported by the JB test. Figure 20 that includes the autocorrelations rejects any suspicion of serious autocorrelation between the returns with all p-values equal to zero.

The IGARCH with t-distribution assumption could not be estimated for the TD7 1 month price returns.

As per Tables 38 and 39, the best parametric models in terms of statistical accuracy for both long and short positions are GARCH(1, 1)_N, IGARCH(1, 1)_N and TGARCH(1, 1)_N. However, not all TGARCH(1, 1)_N's coefficients were statistically significant. Non-parametric models passed most of the statistical test at the respective confidence levels.

Testing now for economic accuracy, by examining the QLF scores, the models that should be used for TD7_1M's risk management are the non-parametric ones. The results are in place for both long and short positions.

6.2.4.2.1 Value at Risk Statistics

TD7_1M																		
Out of Sample Obs	Average VaR			Minimum VaR			Maximum VaR			Hit Sequence Long %			Hit Sequence Short %					
	465	1%	5%	10%	1%	5%	10%	1%	5%	10%	1%	5%	10%	1%	5%	10%		
Model																		
GARCH (1,1)_N	-6.51%	-4.61%	-3.59%	-26.05%	-18.42%	-14.36%	-4.54%	-3.21%	-2.50%	1.72%	3.23%	4.30%	1.72%	2.37%	3.44%			
GARCH (1,1)_T	-8.98%	-6.35%	-4.94%	-132.25%	-93.47%	-72.80%	-0.18%	-0.12%	-0.10%	3.01%	3.87%	4.52%	3.01%	3.44%	3.87%			
GARCH (1,1)_GED	-2.79%	-2.56%	-2.28%	-34.46%	-31.62%	-28.10%	-0.88%	-0.81%	-0.72%	5.38%	5.38%	5.59%	5.38%	6.02%	6.24%			
IGARCH (1,1)_N	-7.04%	-4.98%	-3.88%	-20.09%	-14.21%	-11.07%	-2.86%	-2.02%	-1.58%	2.15%	3.01%	4.52%	1.72%	3.44%	4.09%			
IGARCH (1,1)_T	-6.77%	-4.78%	-3.72%	-8.29%	-5.86%	-4.56%	-4.10%	-2.90%	-2.26%	2.37%	3.23%	3.87%	1.94%	2.80%	4.09%			
IGARCH (1,1)_GED	-5.02%	-4.61%	-4.10%	-6.79%	-6.23%	-5.54%	-2.35%	-2.16%	-1.92%	3.01%	3.23%	3.44%	3.23%	3.44%	4.09%			
(GJR)TGARCH (1,1)_N	-6.51%	-4.60%	-3.59%	-26.46%	-18.71%	-14.58%	-4.52%	-3.19%	-2.49%	1.72%	3.44%	4.30%	1.72%	2.37%	3.44%			
(GJR)TGARCH (1,1)_T																		
(GJR)TGARCH (1,1)_G	-3.32%	-3.05%	-2.71%	-36.46%	-33.46%	-29.74%	-2.04%	-1.87%	-1.66%	4.73%	4.73%	5.38%	4.52%	4.52%	5.16%			
EGARCH (1,1)_N	-5.79%	-4.09%	-3.19%	-22.64%	-16.01%	-12.48%	-3.38%	-2.39%	-1.86%	2.58%	3.87%	5.16%	2.15%	3.23%	4.09%			
EGARCH (1,1)_T	-35.69%	-25.23%	-19.65%	-133.73%	-94.51%	-73.61%	-8.80%	-6.22%	-4.85%	0.22%	0.43%	0.65%	0.22%	0.22%	0.86%			
EGARCH (1,1)_GED	-3.98%	-3.65%	-3.24%	-108.30%	-99.38%	-88.34%	-1.24%	-1.14%	-1.01%	4.09%	4.09%	4.52%	3.01%	4.09%	4.52%			
APARCH (1,1)_N	-5.59%	-3.96%	-3.08%	-24.66%	-17.44%	-13.59%	-1.38%	-0.97%	-0.76%	2.58%	4.30%	4.73%	1.94%	3.23%	4.73%			
APARCH (1,1)_T	-2.21%	-1.56%	-1.22%	-21.65%	-15.30%	-11.92%	-0.01%	-0.01%	0.00%	6.02%	6.88%	7.31%	7.10%	8.39%	9.03%			
APARCH (1,1)_GED	-2.53%	-2.33%	-2.07%	-19.64%	-18.02%	-16.02%	-0.94%	-0.91%	-0.86%	5.38%	5.59%	5.59%	4.52%	5.38%	6.24%			
TARCH (1,1)_X_N	-7.01%	-4.96%	-3.87%	-84.08%	-59.46%	-46.34%	-0.03%	-0.02%	-0.02%	3.01%	4.52%	4.73%	2.80%	3.23%	4.09%			
TARCH (1,1)_X_T	-8.00%	-5.65%	-4.40%	-98.19%	-69.40%	-54.05%	-0.10%	-0.07%	-0.06%	3.01%	4.09%	4.52%	2.58%	3.01%	3.66%			
TARCH (1,1)_X_GED	-3.51%	-3.22%	-2.86%	-30.63%	-28.11%	-24.99%	-1.59%	-1.52%	-1.44%	4.30%	4.73%	4.95%	4.09%	4.30%	4.73%			
RISK METRICS	-6.36%	-4.50%	-3.51%	-28.83%	-20.39%	-15.89%	-2.11%	-1.50%	-1.17%	2.80%	3.87%	4.52%	2.37%	4.09%	4.95%			
HS(100) Long	-15.84%	-2.88%	-0.62%	-36.10%	-7.41%	-2.18%	-2.82%	-0.86%	0.00%	1.08%	4.95%	8.39%	-	-	-			
HS(250) Long	-10.01%	-2.59%	-0.71%	-12.52%	-3.54%	-1.10%	-4.26%	-0.93%	0.00%	1.51%	4.73%	8.60%	-	-	-			
HS(FS) Long	-9.24%	-3.76%	-2.16%	-9.65%	-3.82%	-2.29%	-8.79%	-3.64%	-2.06%	1.72%	3.87%	4.95%	-	-	-			
HS(100) Short	20.73%	7.88%	4.35%	14.31%	2.99%	0.95%	36.10%	10.79%	7.47%	-	-	-	0.43%	1.94%	4.52%			
HS(250) Short	9.35%	2.45%	0.97%	3.18%	1.71%	0.00%	10.92%	3.35%	1.37%	-	-	-	1.51%	5.59%	9.89%			
HS(FS) Short	9.10%	3.81%	2.24%	8.75%	3.70%	2.17%	9.61%	4.04%	2.50%	-	-	-	1.29%	3.44%	6.02%			

Table 37: Represents Value at Risk results for TD7 route 1 month price returns. The first column presents the different model types that used to measure Value at Risk. The next nine columns present average, minimum and maximum VaR estimates at 1%, 5% and 10%, confidence levels, respectively. The last six columns present the HIT sequence as a percentage of the out-of-sample observations. HIT sequences are reported for both long and short positions.

6.2.4.3 FFA 3 Months

As per Table 6 TD7 3 Months' historical distribution is leptokurtic and highly skewed at the left side (Fischer Skewness Statistic equals -3.65). In fact, TD7_3M presents the highest skewness between all returns time series under investigation. Figure 20 that includes the autocorrelations rejects the presence of any serious autocorrelation between the returns with all p-values equal to zero.

The IGARCH with t-distribution assumption could not be estimated for the TD7 3 months price returns.

Tables 41 and 42, suggest that all models fail to pass the statistical tests at VaR10% with the parametric ones failing also at VaR1%. Same confirmed for both long and short positions. This models' incapacity to capture the risk is depicted also from Table 40 that presents the HIT sequences. Combining this finding with the high negative skewness, the models incapacity to adapt to highly non-normal distributions can be justified.

For long positions, all HS(100), HS(250) and HS(FS) captured the risk, while for short ones only the HS(FS). The parametric models performed well only at VaR5%.

6.2.4.3.1 Value at Risk Statistics

Out of Sample Obs	TD7_3M															
	Average VaR			Minimum VaR			Maximum VaR			Hit Sequence Long %			Hit Sequence Short %			
	465	1%	5%	10%	1%	5%	10%	1%	5%	10%	1%	5%	10%	1%	5%	10%
Model																
GARCH (1,1)_N	-3.18%	-2.25%	-1.75%	-4.92%	-3.48%	-2.71%	-2.21%	-1.56%	-1.22%	2.15%	3.01%	3.66%	2.80%	4.09%	5.16%	
GARCH (1,1)_T	-1.42%	-1.00%	-0.78%	-10.96%	-7.74%	-6.03%	-0.03%	-0.02%	-0.02%	4.95%	5.81%	5.81%	6.45%	7.10%	7.74%	
GARCH (1,1)_GED	-1.55%	-1.43%	-1.27%	-7.81%	-7.17%	-6.37%	-1.13%	-1.04%	-0.92%	4.52%	4.52%	4.73%	5.38%	5.38%	5.81%	
IGARCH (1,1)_N	-3.04%	-2.15%	-1.67%	-4.77%	-3.38%	-2.63%	-1.84%	-1.30%	-1.02%	2.37%	3.23%	3.87%	3.01%	3.87%	5.59%	
IGARCH (1,1)_T	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	
IGARCH (1,1)_GED	-2.24%	-2.06%	-1.83%	-3.97%	-3.64%	-3.24%	-1.14%	-1.05%	-0.93%	3.01%	3.23%	3.87%	4.30%	4.73%	5.59%	
(GJR)TGARCH (1,1)_N	-3.28%	-2.32%	-1.81%	-4.90%	-3.47%	-2.70%	-2.24%	-1.58%	-1.23%	2.15%	3.01%	3.66%	2.80%	4.09%	4.95%	
(GJR)TGARCH (1,1)_T	-1.94%	-1.37%	-1.07%	-14.90%	-10.53%	-8.20%	-0.12%	-0.08%	-0.06%	3.87%	4.95%	5.81%	4.95%	6.67%	6.88%	
(GJR)TGARCH (1,1)_G	-1.85%	-1.70%	-1.51%	-10.12%	-9.28%	-8.25%	-1.46%	-1.34%	-1.19%	4.09%	4.52%	4.52%	4.52%	4.95%	5.38%	
EGARCH (1,1)_N	-3.04%	-2.15%	-1.67%	-4.27%	-3.02%	-2.35%	-2.37%	-1.67%	-1.30%	2.37%	3.23%	3.87%	3.01%	3.87%	4.95%	
EGARCH (1,1)_T	-19.04%	-13.45%	-10.48%	-4128.76%	-2917.97%	-2272.68%	-0.96%	-0.68%	-0.53%	4.09%	4.52%	4.52%	4.95%	6.02%	6.45%	
EGARCH (1,1)_GED	-1.85%	-1.70%	-1.51%	-10.12%	-9.28%	-8.25%	-1.46%	-1.34%	-1.19%	4.09%	4.52%	4.52%	4.52%	4.95%	5.38%	
APARCH (1,1)_N	-2.94%	-2.08%	-1.62%	-4.31%	-3.05%	-2.37%	-2.14%	-1.51%	-1.18%	2.15%	3.44%	3.66%	3.23%	4.52%	4.95%	
APARCH (1,1)_T	-0.70%	-0.49%	-0.38%	-7.98%	-5.64%	-4.39%	-0.01%	0.00%	0.00%	5.38%	5.38%	6.02%	7.31%	7.96%	8.39%	
APARCH (1,1)_GED	-1.86%	-1.71%	-1.52%	-10.75%	-9.86%	-8.76%	-1.45%	-1.33%	-1.18%	3.66%	4.30%	4.52%	4.30%	4.95%	5.38%	
TARCH (1,1)_X_N	-3.22%	-2.28%	-1.77%	-4.96%	-3.51%	-2.73%	-2.13%	-1.50%	-1.17%	2.15%	3.01%	3.66%	2.80%	4.09%	5.16%	
TARCH (1,1)_X_T	-1.24%	-0.88%	-0.68%	-10.38%	-7.34%	-5.71%	-0.01%	-0.01%	-0.01%	4.95%	5.81%	6.02%	6.67%	7.31%	7.74%	
TARCH (1,1)_X_GED	-2.33%	-2.14%	-1.90%	-6.10%	-5.59%	-4.97%	-1.69%	-1.55%	-1.38%	3.01%	3.01%	3.66%	3.01%	3.87%	4.73%	
RISK METRICS	-2.87%	-1.49%	-1.16%	-8.08%	-5.71%	-4.45%	-0.51%	0.00%	0.00%	2.37%	4.52%	4.73%	3.87%	36.99%	37.63%	
HS(100) Long	-5.68%	-1.89%	-0.19%	-8.10%	-4.31%	-0.75%	-2.02%	0.00%	0.00%	1.08%	4.09%	7.74%	-	-	-	
HS(250) Long	-5.62%	-1.50%	-0.17%	-8.00%	-2.11%	-0.60%	-3.47%	-1.08%	0.00%	1.08%	4.09%	7.10%	-	-	-	
HS(FS) Long	-5.19%	-2.30%	-1.18%	-5.23%	-2.38%	-1.32%	-5.13%	-2.22%	-1.12%	0.86%	3.01%	4.52%	-	-	-	
HS(100) Short	7.65%	4.74%	2.69%	5.51%	1.94%	0.00%	8.00%	5.61%	4.82%	-	-	-	0.65%	1.72%	16.77%	
HS(250) Short	5.61%	1.47%	0.46%	3.64%	0.00%	0.00%	7.26%	2.35%	1.13%	-	-	-	1.29%	5.59%	30.11%	
HS(FS) Short	5.11%	2.29%	1.21%	4.88%	2.26%	1.13%	5.23%	2.30%	1.33%	-	-	-	1.51%	3.87%	6.02%	

Table 40: Represents Value at Risk results for TD7 route 3 months price returns. The first column presents the different model types that used to measure Value at Risk. The next nine columns present average, minimum and maximum VaR estimates at 1%, 5% and 10%, confidence levels, respectively. The last six columns present the HIT sequence as a percentage of the out-of-sample observations. HIT sequences are reported for both long and short positions.

Chapter 7: Conclusion

The study reveals that all routes' spot, 1 month and 3 months front historical distributions of returns are leptokurtic and skewed compared to the theoretical Normal distribution. This characteristic may reflect a degree of the tanker markets inefficiency due to the observed mysticopathy regarding the concluded transactions. This finding should be taken into consideration from market participants, when establishing a risk management framework, since assumptions regarding the distributions may have a considerable impact on Value at Risk estimates, valuations of financial instrument and hedging practices. Research between spot and future contact prices revealed that not one type of skewness is maintained along spot and future contract returns of the same route. This finding observed at TC2, TD3 and TD7. Additionally, sample period future contracts price returns presented less volatility than spot's, with only exemption the future contract price returns of route TC5.

Values at Risk results justify the importance of the selection of the method for calculating the conditional volatility, since in many cases the several Value at Risk methods presented significantly different values with each other. According to the Value at Risk backtesting results, neither the extra complexity nor the extended distribution assumptions managed to improve the performance of the simple GARCH model. It is remarkable that there was no Value at Risk method, assuming a Generalized Error Distributions of returns, which managed to capture the risk at 1% confidence level. This is explained from the fact that generalized error distributions assumption weighs heavily the excess peak characteristic but not the fat tails, in comparison with Normal and Student distributions. The results also suggest that neither the augmented TGARCH model that incorporated the spot-3 months front returns slop, managed to improve simplest GARCH model's ability to capture the risk.

Findings support that freight rate risk quantification favors simpler specifications, such as the GARCH and the historical simulation models. The results are congruent with findings from earlier periods by Kavussanos and

Dimitrakopoulos (2011) and Angelidis and Skiadopoulos (2008), who applied similar methodologies on freight indexes and spot price returns. This study extends this verification to also shipping freight futures contracts and short positions in both spot and futures markets.

To the best of author's knowledge, it is the first time that a study measures the performance between several parametric and non-parametric models in the tanker freight futures markets. Also, there are hardly any studies comparing the results between long and short positions. It will be of high research interest for further studies to examine if hybrid models, like semi-parametric or GARCH-EVT could present better results in capturing the risk of shipping freight futures contracts. It would be also interesting, to examine if different approaches, such as the Chaos Theory, could contribute to the methodology of modelling volatility and establishing risk management frameworks for the tanker freight markets.

Chapter 8: List of References

- Abouarghoub, W. M., & Mariscal, I. B. F. (2011). Measuring level of risk exposure in tanker Shipping freight markets. *International Journal of Business and Social Research*, 1(1), pp. 20-44.
- Abouarghoub, Wessam. "Measuring Shipping Tanker Freight Risk."
- Alizadeh, A., & Nomikos, N. (2007b). The Slope of Forward Curve and Volatility of Shipping Freight Rates', mimeo, Cass Business School, City University, London, UK.
- Alizadeh, A., & Nomikos, N. (2009). Shipping derivatives and risk management. Palgrave Macmillan.
- Andreou, E. & E. Ghysels (2002). Rolling-Sample Volatility Estimators. *Journal of Business & Economic Statistics*, 20, pp. 363-376.
- Angelidis, T., Benos, A., & Degiannakis, S. (2004). The use of GARCH models in VaR estimation. *Statistical methodology*, 1(1), pp. 105-128.
- Angelidis, T., & Skiadopoulos, G. (2008). Measuring the market risk of freight rates: a value-at-risk approach. *International Journal of Theoretical and Applied Finance*, pp. 447-469.
- Bodie, Z., A. Kane & A. J. Marcus. (2009). Investments. New York: Mc Graw Hill.
- Bollerslev, T. (1986). Generalized Autoregressive Conditional Heteroskedasticity, *Journal of Econometrics*, 31. pp. 307-327.
- Bonett, D. G. & E. Seier (2002). A test of normality with high uniform power. *Computational Statistics & Data Analysis*, pp. 435 – 445.
- Bookstaber, R. M. & S. Pomerantz (1989). An Information-Based Model of Market Volatility. *Financial Analysts Journal*, 45, pp. 37-46.
- Bowman, K. O. & L. R. Shenton (1975). Omnibus test contours for departures from normality based on b1 and b2. *Biometrika*, 62, pp. 243-250.
- Brooks, C. (2008). Introductory Econometrics for Finance. Cambridge: *Cambridge University Press*.
- D'Agostino, R. B., A. Belanger & R. B. D'Agostino, Jr. (1990). A Suggestion for Using Powerful and Informative Tests of Normality. *The American Statistician*, Vol. 44, pp. 316-321.

- Danielsson, J. (2011). Financial Risk Forecasting. WILEY, London.
- Ding, Z., Granger, C. W., & Engle, R. F. (1993). A long memory property of stock market returns and a new model. *Journal of empirical finance*, 1(1), pp. 83-106.
- Engle, R. (1982). Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation. *Econometrica*, 50(4): pp. 987-1007.
- Fama, E. F. & J. D. MacBeth (1973). Risk, return, and equilibrium: Empirical tests. *The Journal of Political Economy*, 81, pp. 607-636.
- French, K. R., G. W. Schwert & R. F. Stambaugh (1987). Expected stock returns and volatility. *Journal of Financial Economics*, 19, pp. 3-29.
- Gel, Y. R. & J. L. Gastwirth (2008). A robust modification of the Jarque-Bera test of normality. *Economics Letters*, 99, pp. 30-32.
- Gel, Y. R., W. Miao & J. L. Gastwirth (2007). Robust directed tests of normality against heavy-tailed alternatives. Computational Statistics Camp; Data Analysis, 51, pp. 2734-2746.
- Glosten, L., Jagannathan, R. and Runkle, D. (1993). On the Relation between the Expected Value and the Volatility of the Nominal Excess Return on Stocks, *Journal of Finance*, XLVIII. Pp. 1779-1801.
- Hagan, P. S., D. Kumar, A. S. Lesniewski & D. E. Woodward (2002). Managing Smile Risk. *WILMOTT Magazine*, pp. 84-108.
- Haug, E. G. (2007). The Complete Guide to Option Pricing Formulas. New York: The McGraw-Hill Companies, Inc.
- Heston, S. (1993). A closed-form solution for options with stochastic volatility with applications to bond and currency options. *Review of Financial Studies*, 6, pp. 327-343.
- Hull, J. C. (2012). Options, Futures And Other Derivatives. Harlow: Pearson Education Limited.
- Jarque, C. M. & A. K. Bera (1980). Efficient tests for normality, homoscedasticity and serial independence of regression residuals. *Economics Letters*, 6, pp. 255-259.
- Jensen, A. and Lange, T. (2007). Addressing the IGARCH puzzle, *Department of Natural Sciences & Department of Mathematical Sciences*, University of Copenhagen.

- Kavussanos, M. G. & D. N. Dimitrakopoulos (2011). Market risk model selection and medium-term risk with limited data: Application to ocean tanker freight markets. *International Review of Financial Analysis*, 20, pp. 258-268.
- Klein, B. (1977) The Demand for Quality-adjusted Cash Balances: Price Uncertainty in the US Demand for Money Function. *Journal of Political Economy*, Vol. 85, pp. 692-715.
- Kupiec, P.H. (1995). Techniques for verifying the accuracy of risk measurement models. *The Journal of Derivatives*, 3, pp. 73-84.
- Lopez, J.A. (1998). Methods for evaluating Value-at-Risk Estimates. Federal Reserve. Bank of New York. Economic Policy Review.
- Mandelbrot, B. (1963). The Variation of Certain Speculative Prices. *The Journal of Business*, 36, pp. 394-419.
- Mantalos, P. (2010a). Robust Critical Values For The Jarque-Bera Test For Normality. *Jönköping International Business School*.
- Mantalos, P. (2010b). Three Different Measures of Sample Skewness and Kurtosis and their Effects on the Jarque- Bera Test for Normality. *Jönköping International Business School*.
- Mills, F. C. (1927). The Behaviour of Prices. *National Bureau of Economic Research*.
- Nelson, D. (1991). Conditional Heteroskedasticity in Asset Returns: A New Approach, *Econometrica*, 59(2): pp. 347-370.
- Oliver, M. (1926). Les Nombres indices de la variation des prix. *Paris doctoral dissertation*.
- Pearson, K. (1895). Contributions to the Mathematical Theory of Evolution. II. Skew Variation in Homogeneous Material. *Philosophical Transactions of the Royal Society of London*. 186, pp. 343-414.
- Pearson, K. (1905). Das Fehlergesetz und Seine Verallgemeinerungen Durch Fechner und Pearson. A Rejoinder. *Biometrika*, 4, No. 1/2, pp. 169-212.
- Ruppert, D. (1987). What Is Kurtosis?: An Influence Function Approach. *The American Statistician*, 41, pp. 1-5.
- Stopford, M. (2009). Maritime Economics 3e. Routledge.
- Taylor. S. (1986). Modeling financial time series. Chichester, Wiley.

- Terasvirta, T. (2006). An Introduction to Univariate GARCH Models, *SSE/EFI Working papers in Economics and Finance*, 646.
- Thadewald, T. & H. Böning (2007). Jarque–Bera Test and its Competitors for Testing Normality – A Power Comparison. *Journal of Applied Statistics*, 34, pp. 87-105.
- Urzúa, C. M. (1996). On the correct use of omnibus tests for normality. *Economics Letters*, 53, pp. 247-251.

Appendix A

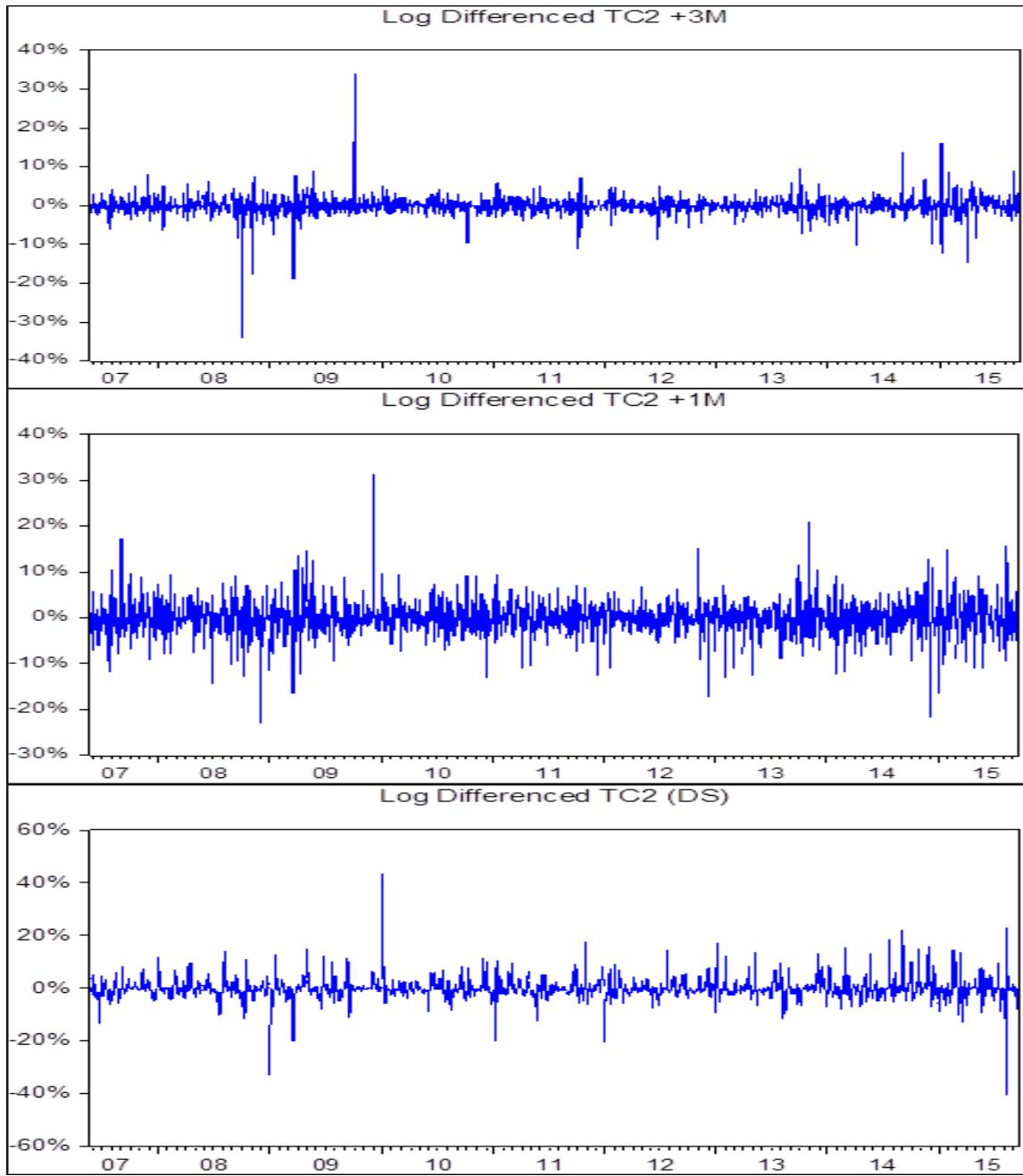


Figure 12: Log Differenced returns of spot, 1 Month front and 3 Months front of the TC2 route

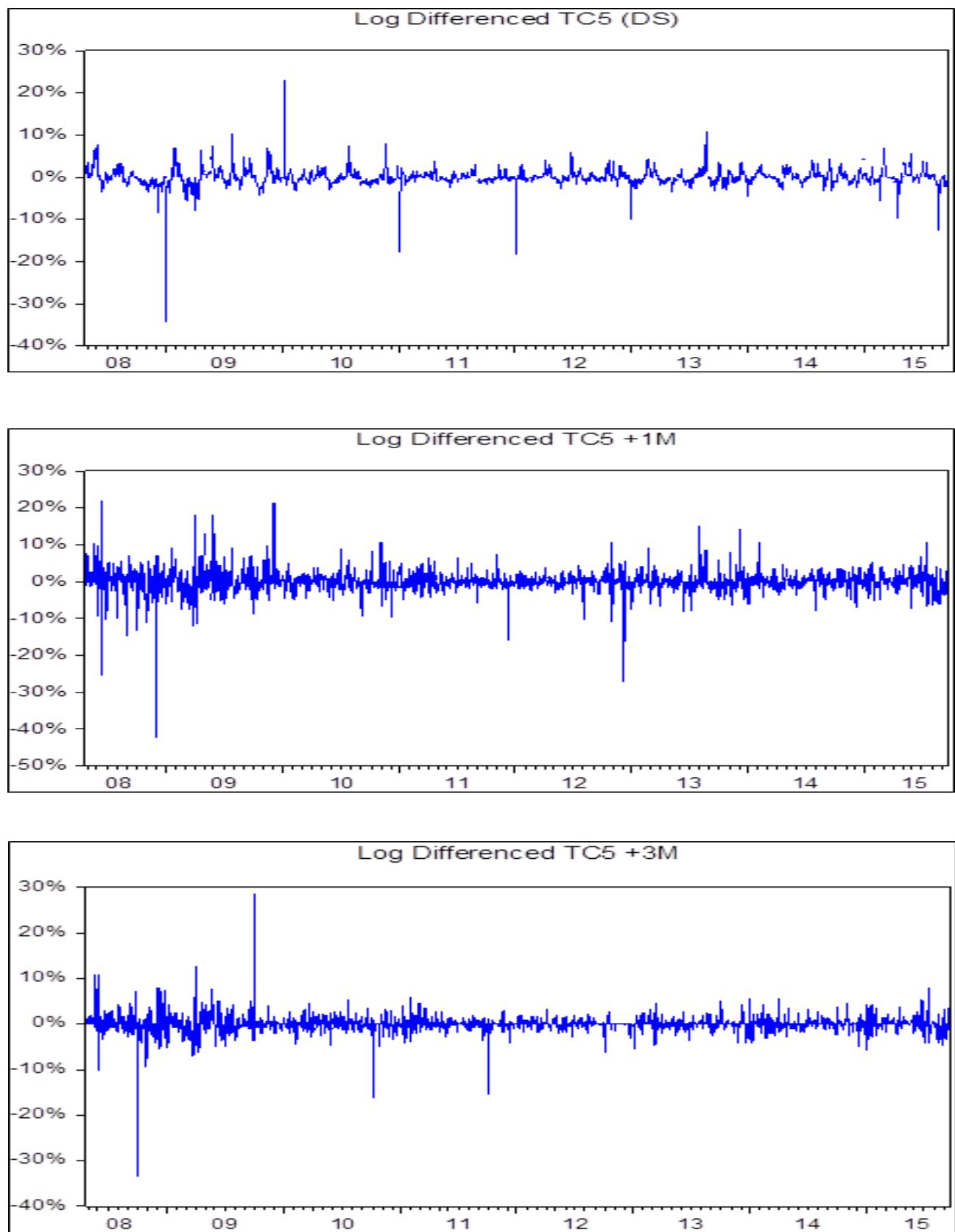


Figure 13: Log Differenced returns of spot, 1 Month front and 3 Months front of the TC5 route

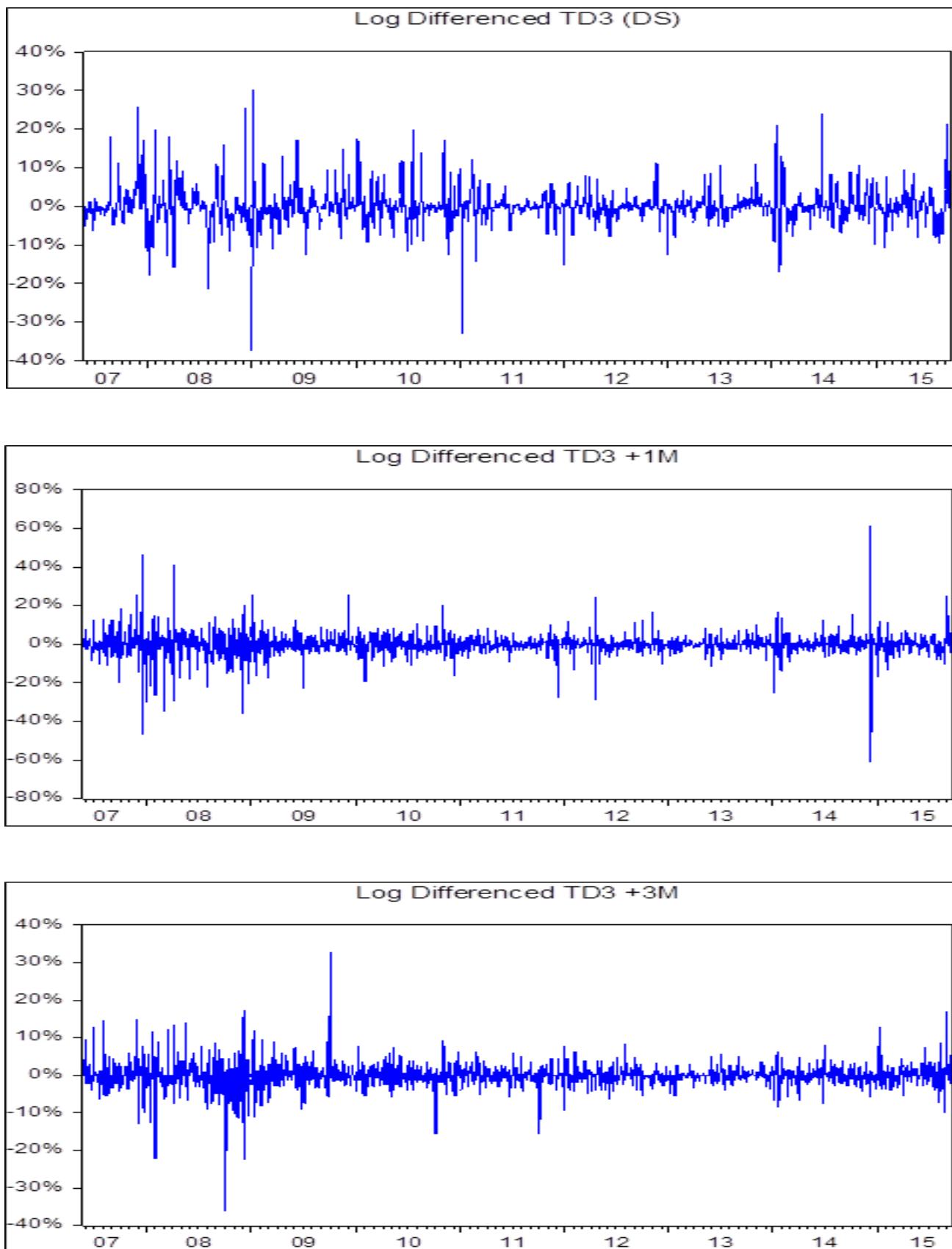


Figure 14: Log Differenced returns of spot, 1 Month front and 3 Months front of the TD3 route

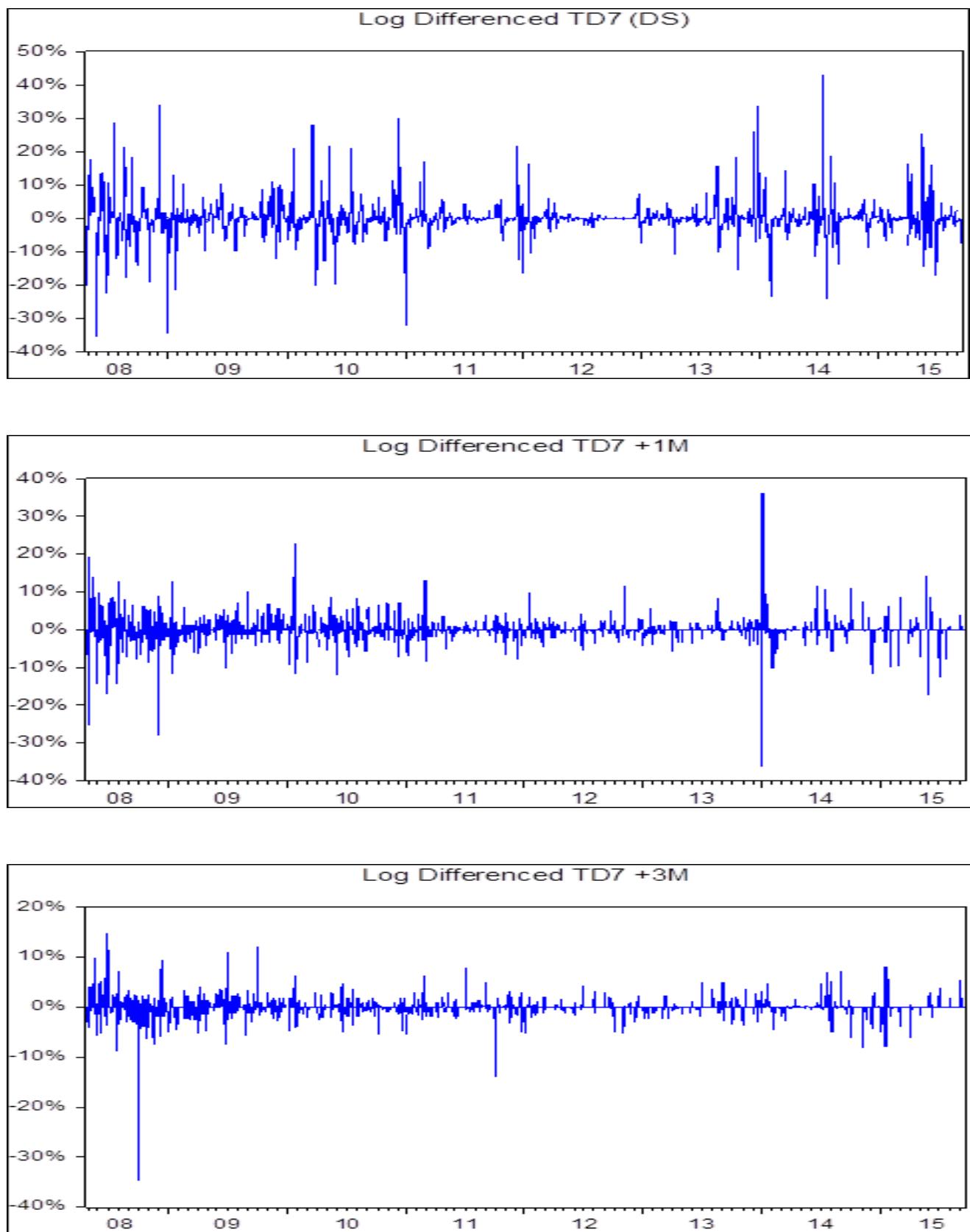


Figure 15: Log Differenced returns of spot, 1 Month front and 3 Months front of the TD7 route

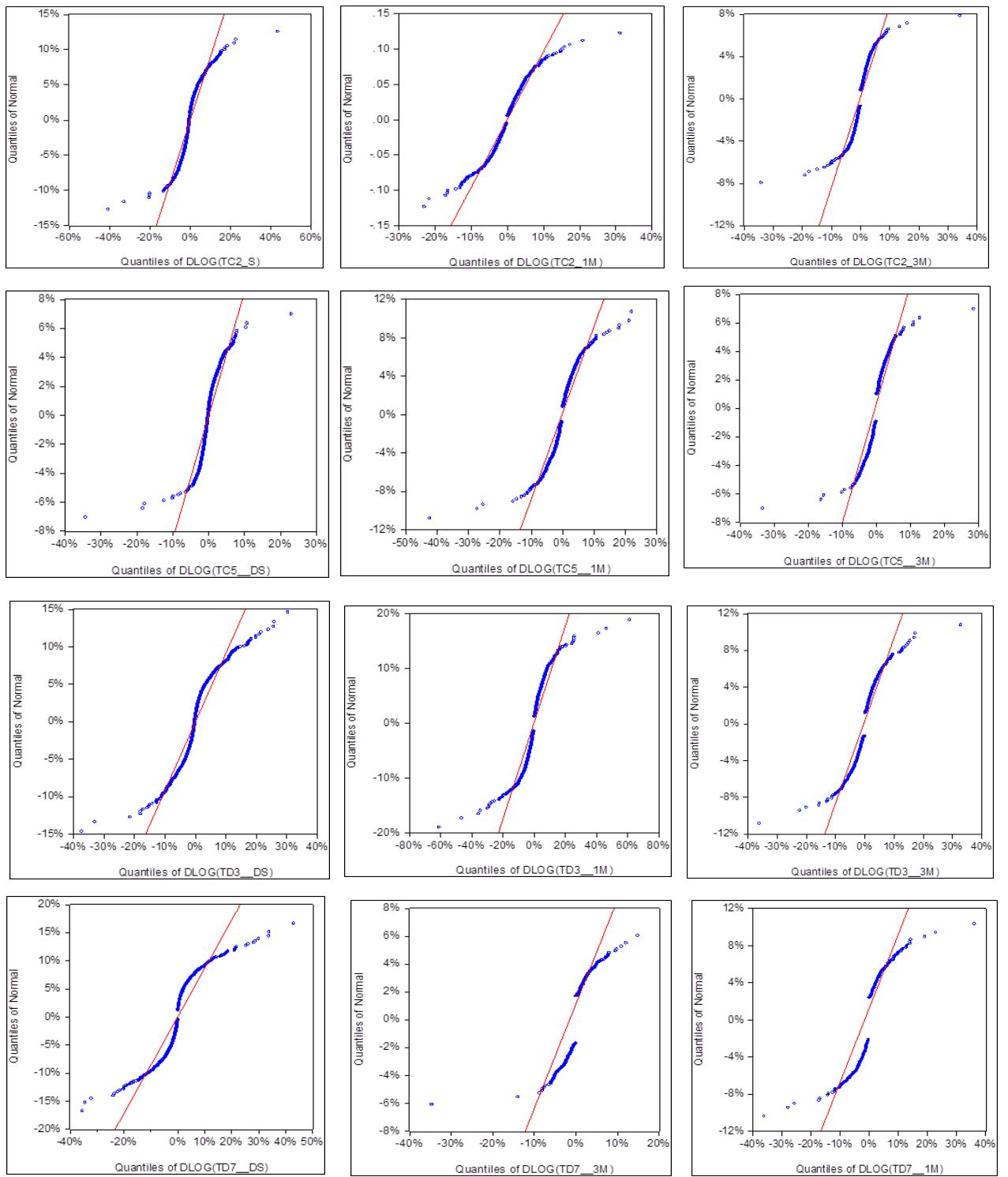


Figure 16: QQ plots for spot, 1 Month front and 3 Months front of TC2, TC5, TD3 and TD7 routes

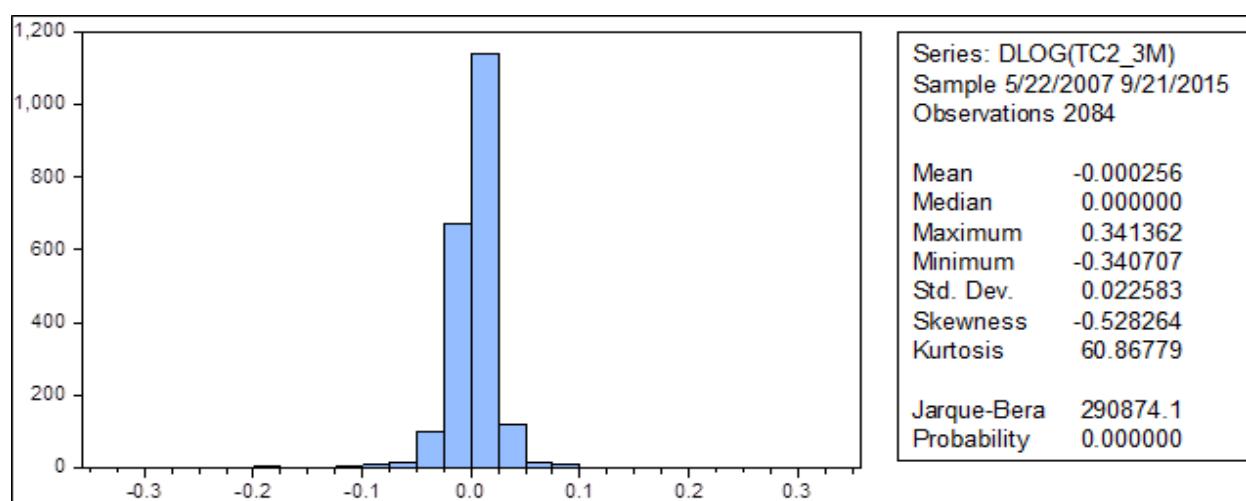
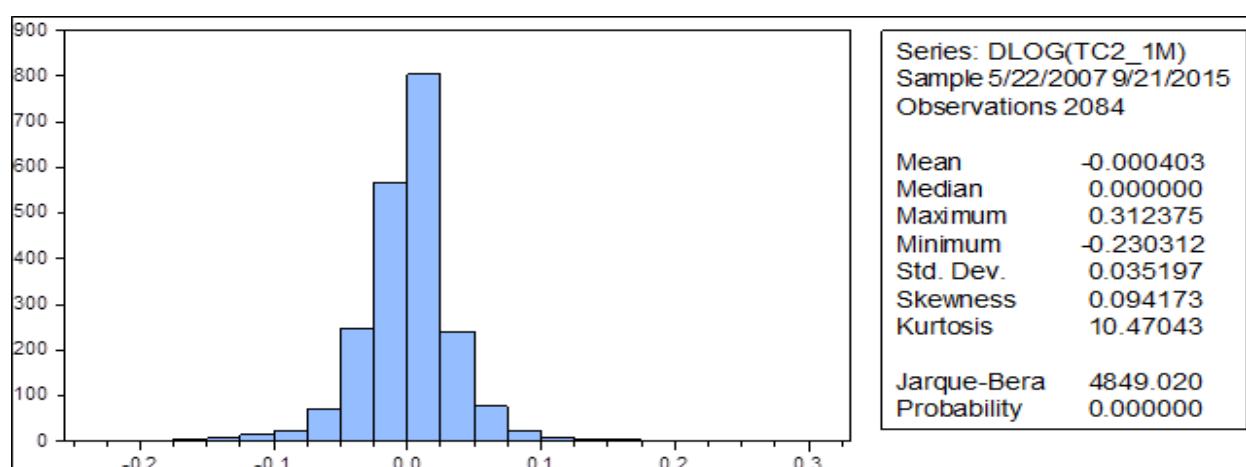
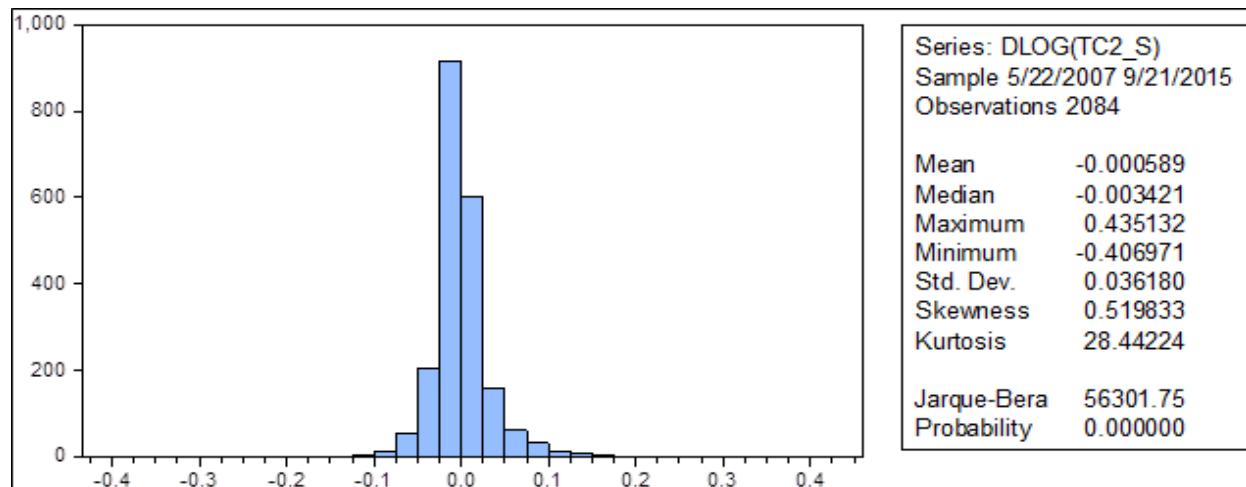


Figure 17: Histograms along with descriptive statistics of the returns of spot, 1 Month front and 3 Months front for TC2 route

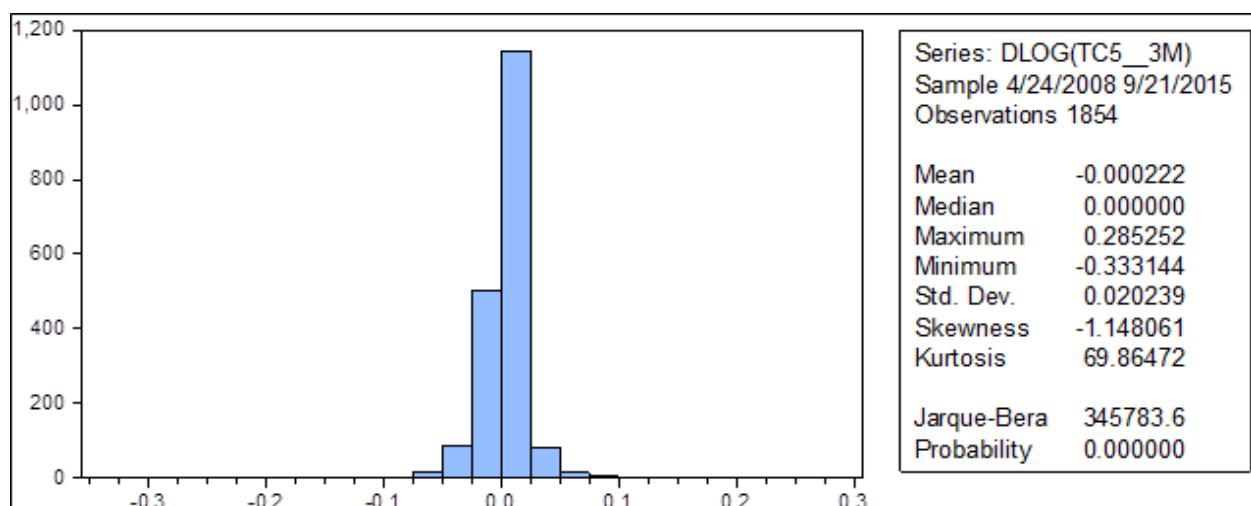
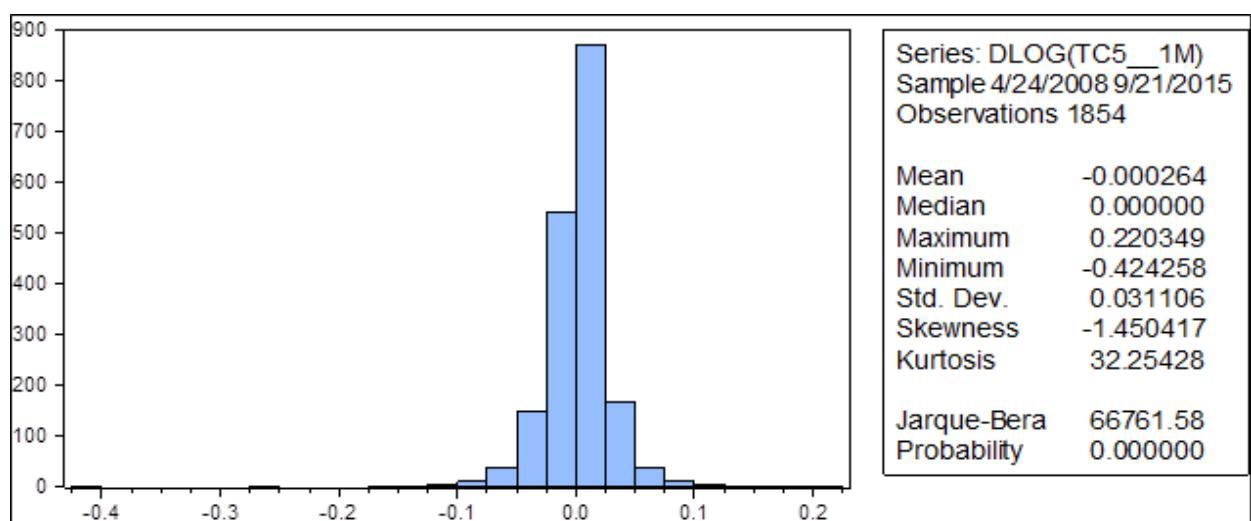
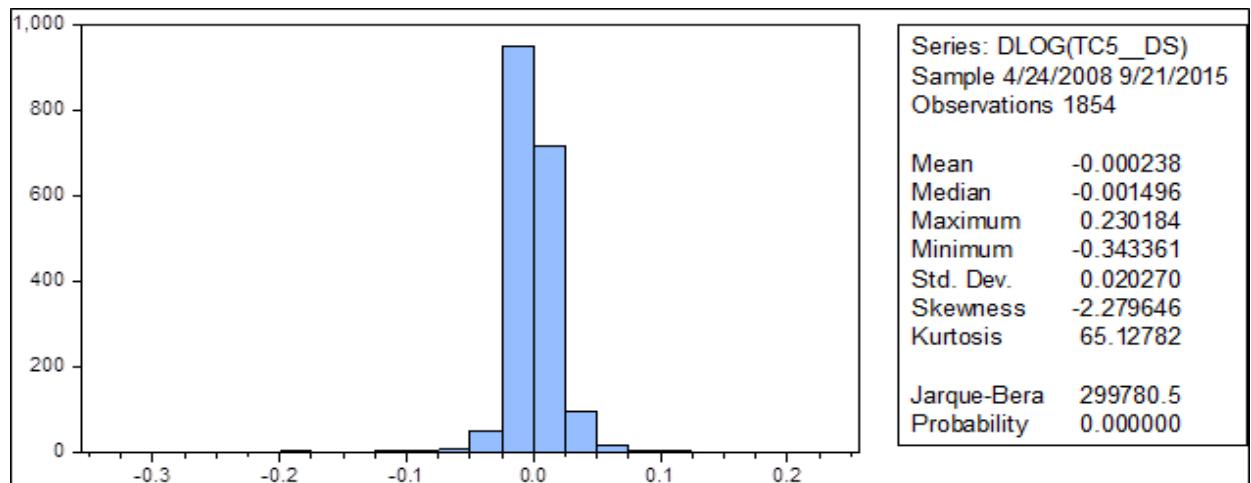


Figure 18: Histograms along with descriptive statistics of the returns of spot, 1 Month front and 3 Months front for TC5 route

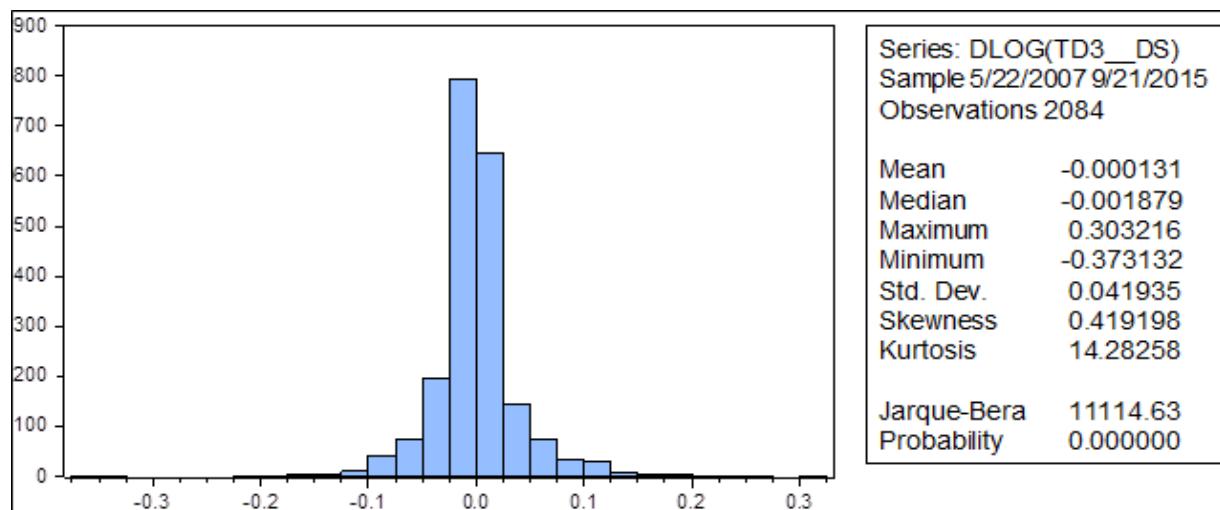
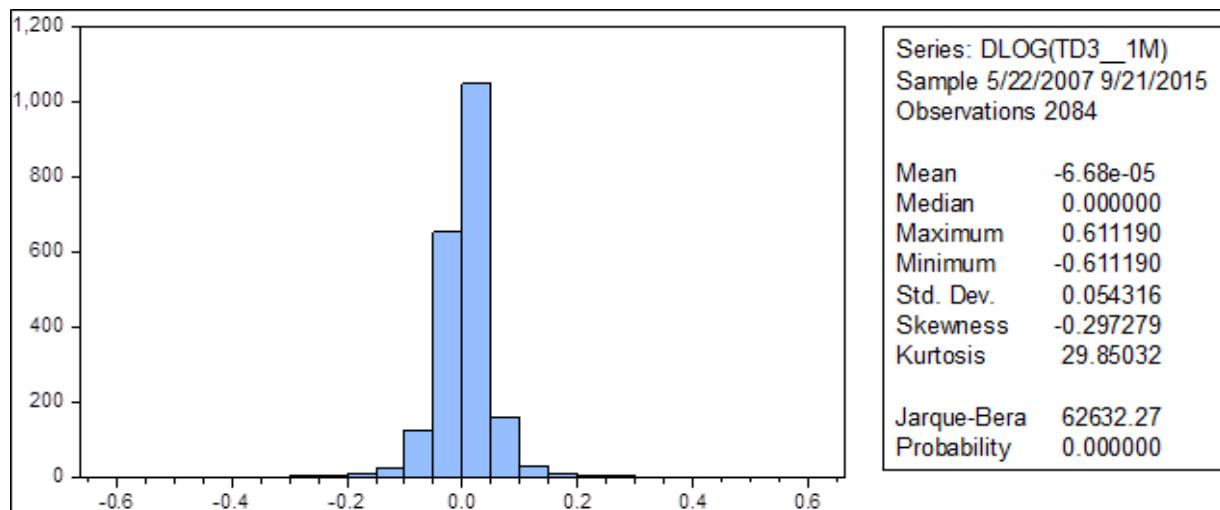
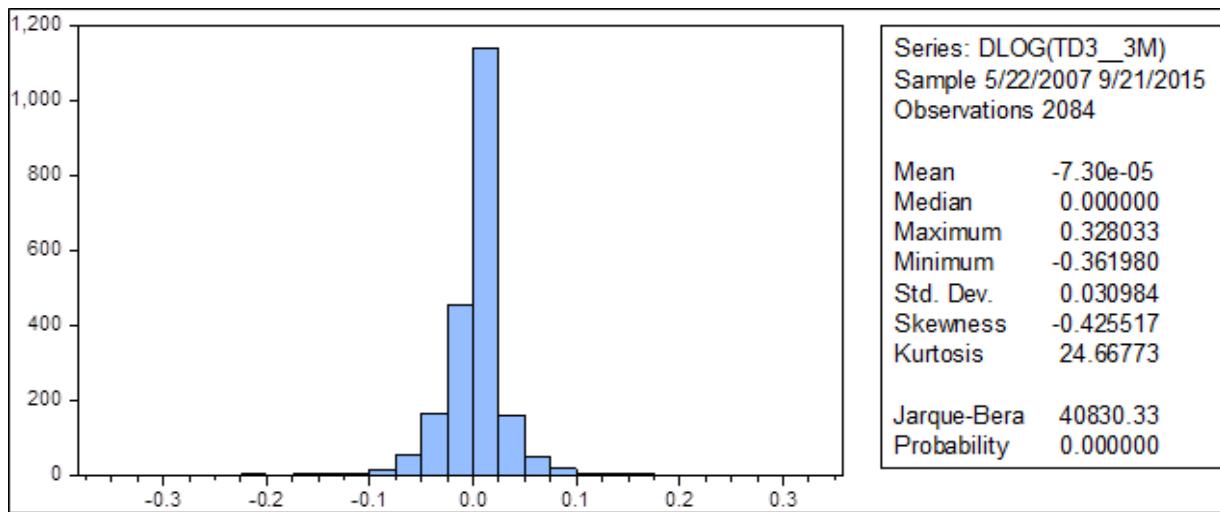


Figure 19: Histograms along with descriptive statistics of the returns of spot, 1 Month front and 3 Months front for TD3 route

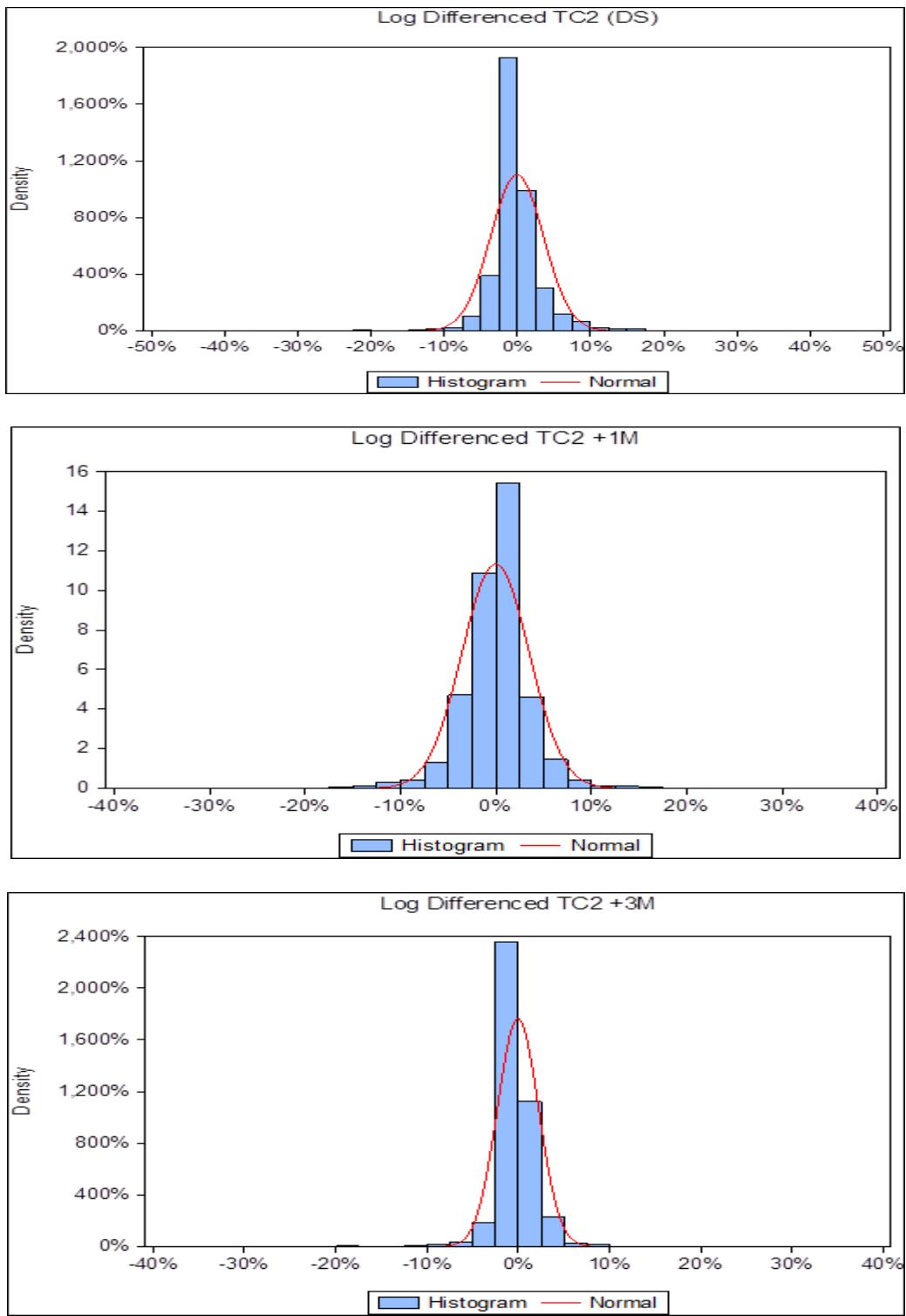


Figure 21: Histograms against the theoretical normal distribution of the returns of spot, 1 Month front and 3 Months front for TC2 route

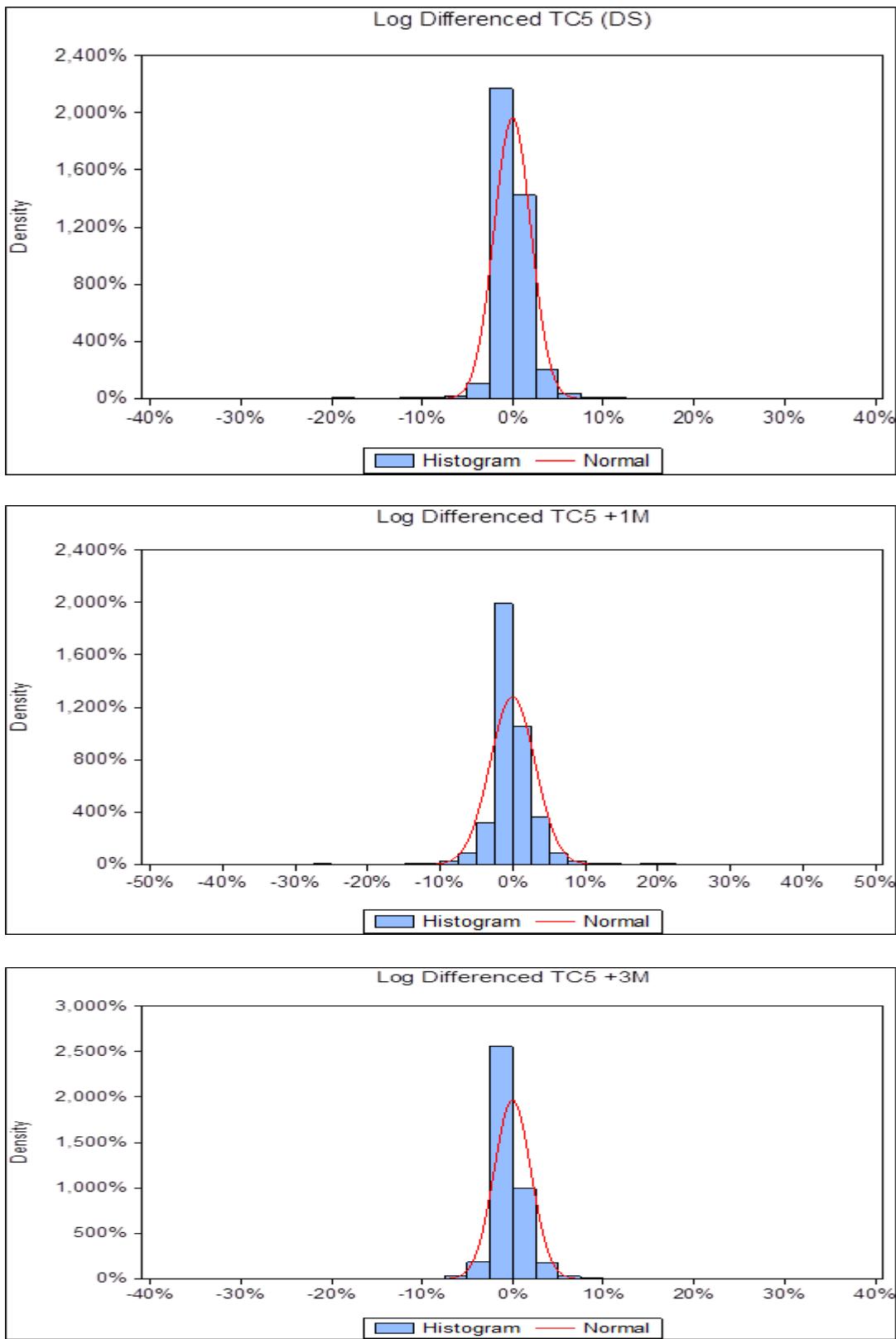


Figure 22: Histograms against the theoretical normal distribution of the returns of spot, 1 Month front and 3 Months front for TC5 route

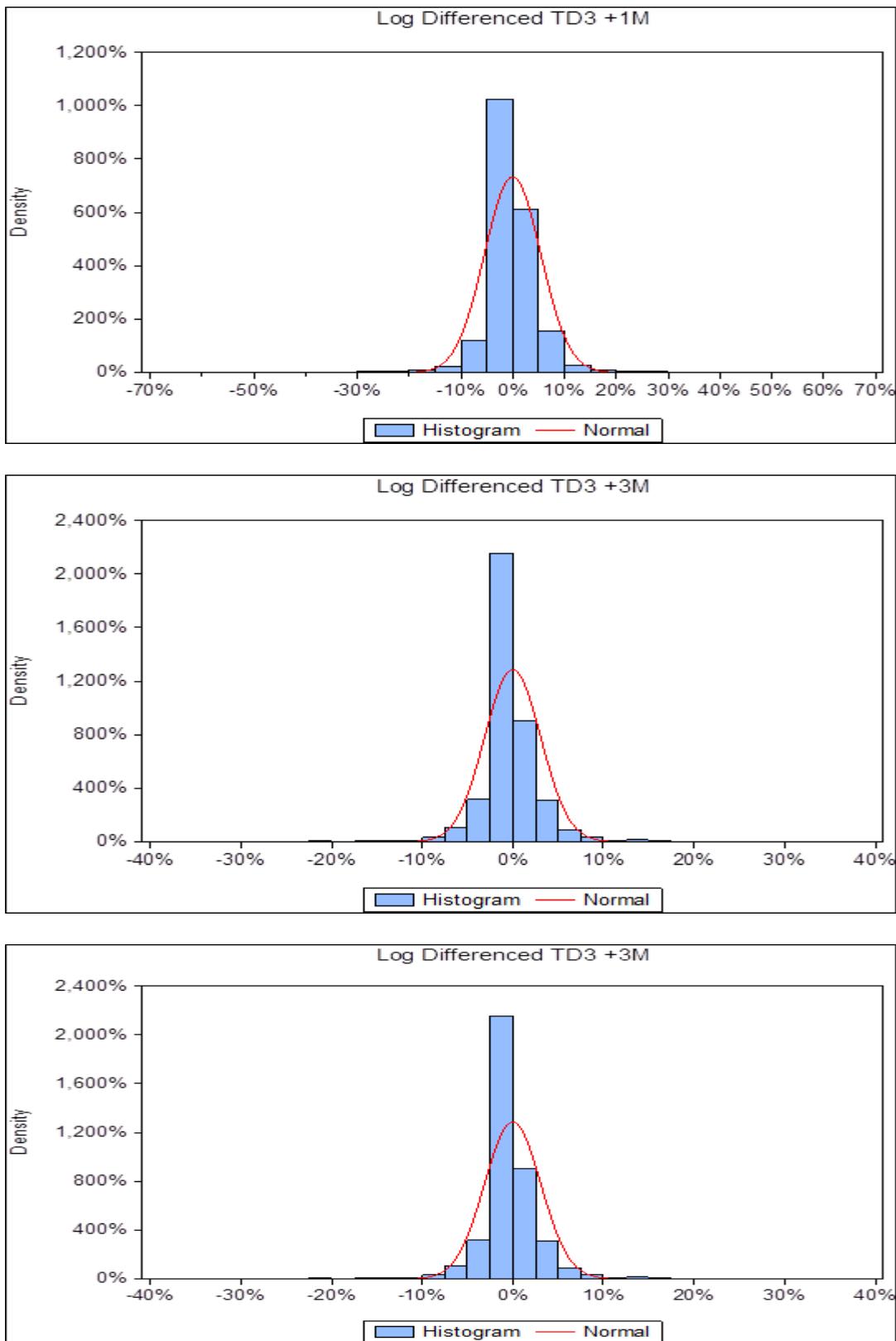


Figure 23: Histograms against the theoretical normal distribution of the returns of spot, 1 Month front and 3 Months front for TD3 route

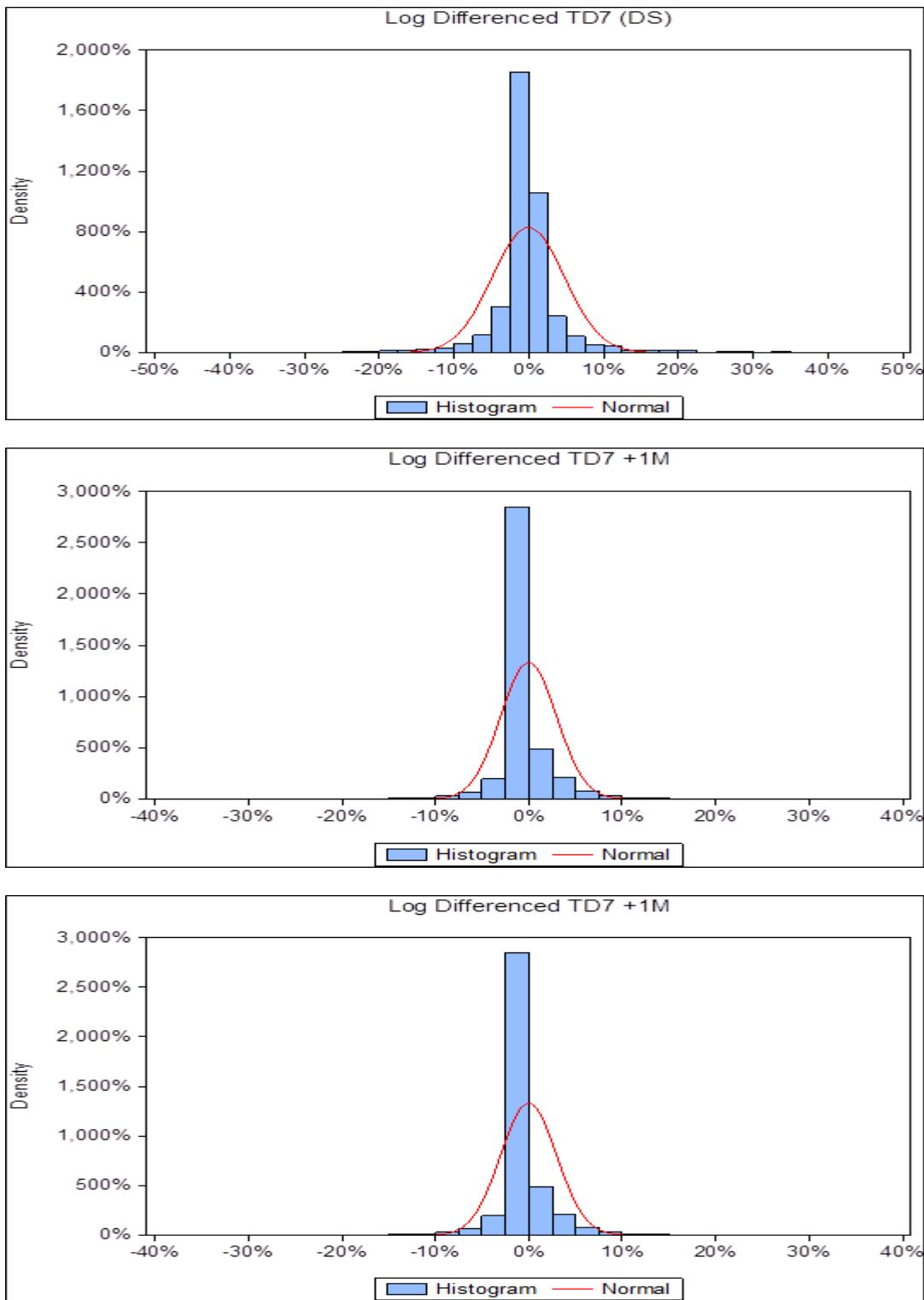
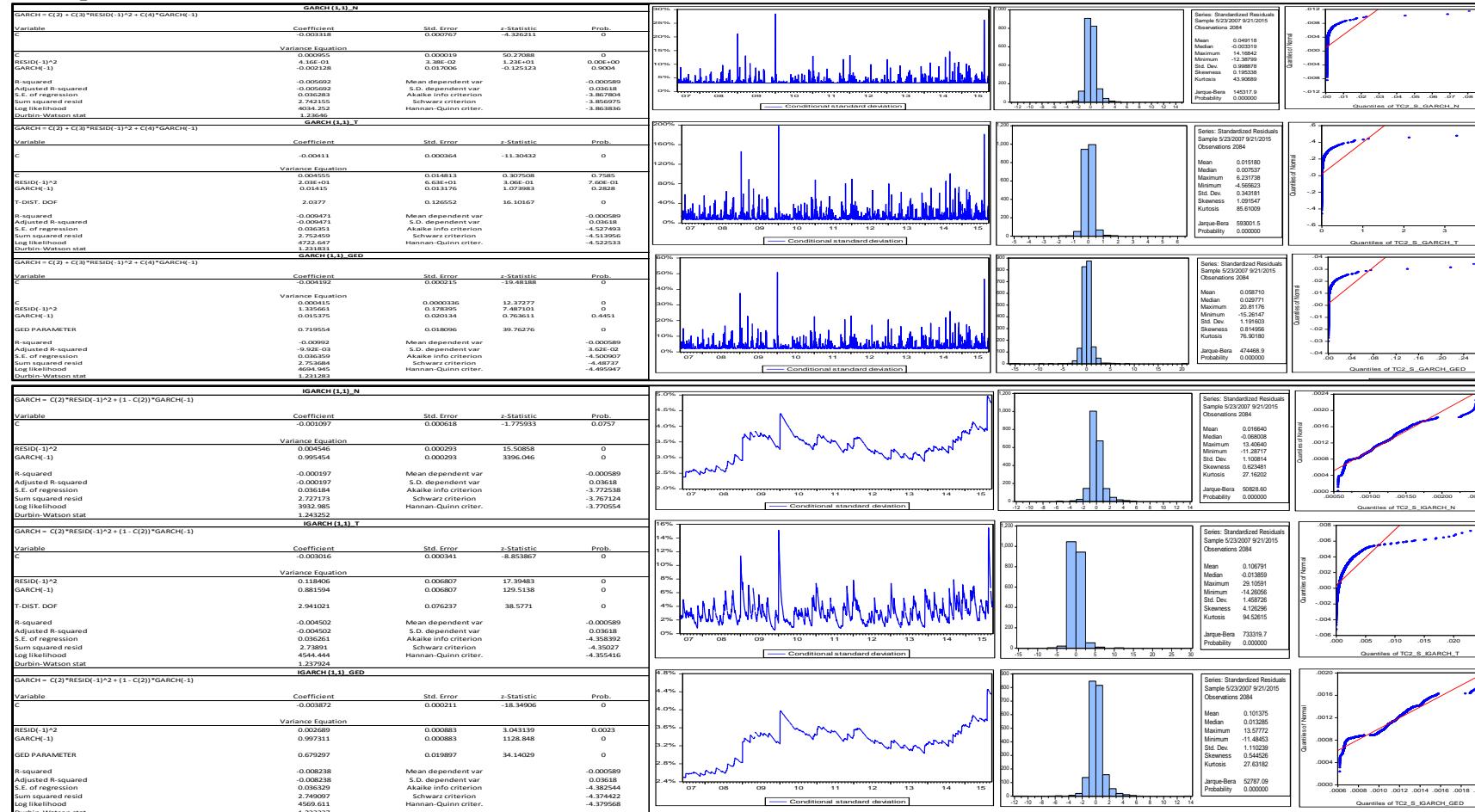
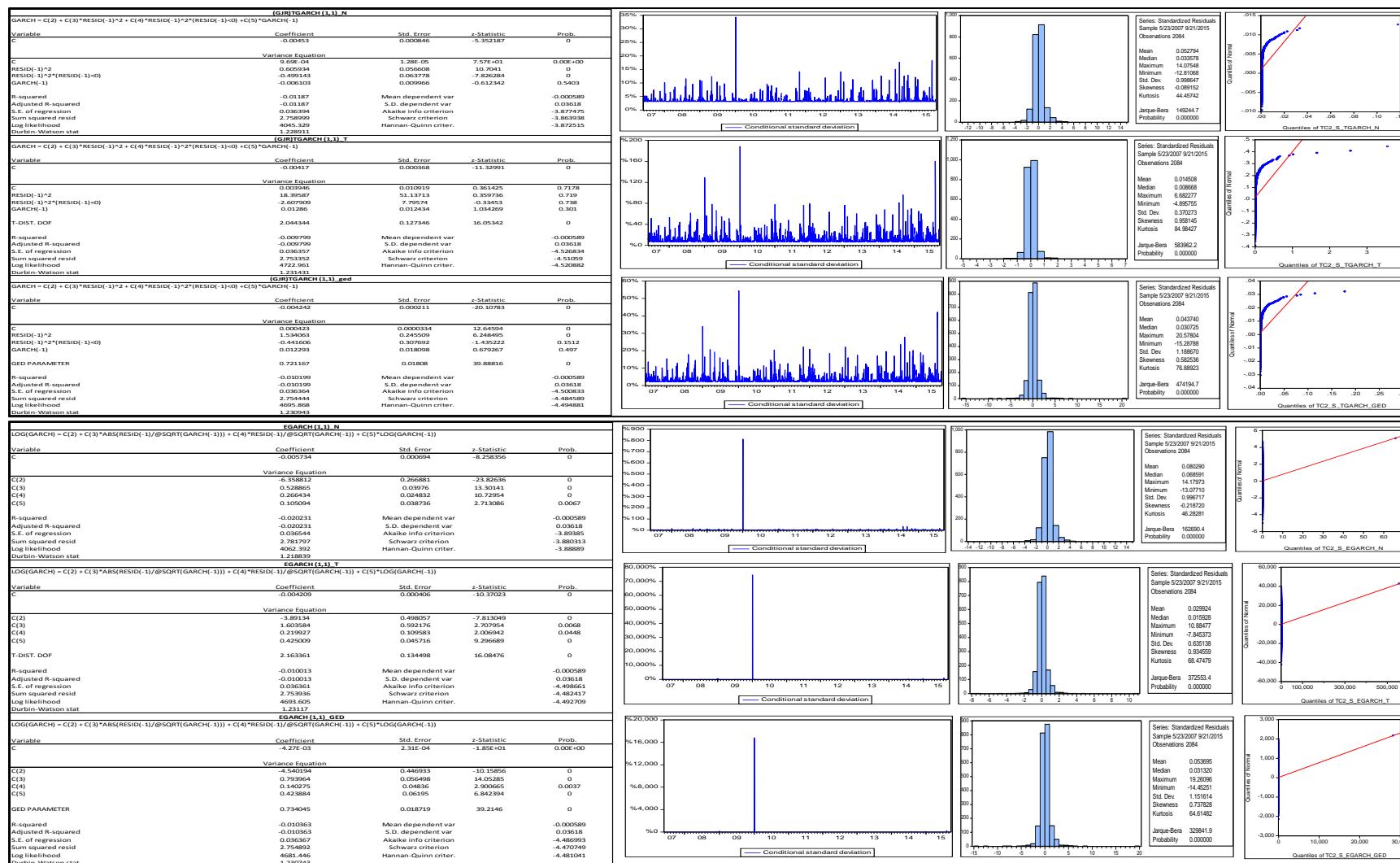


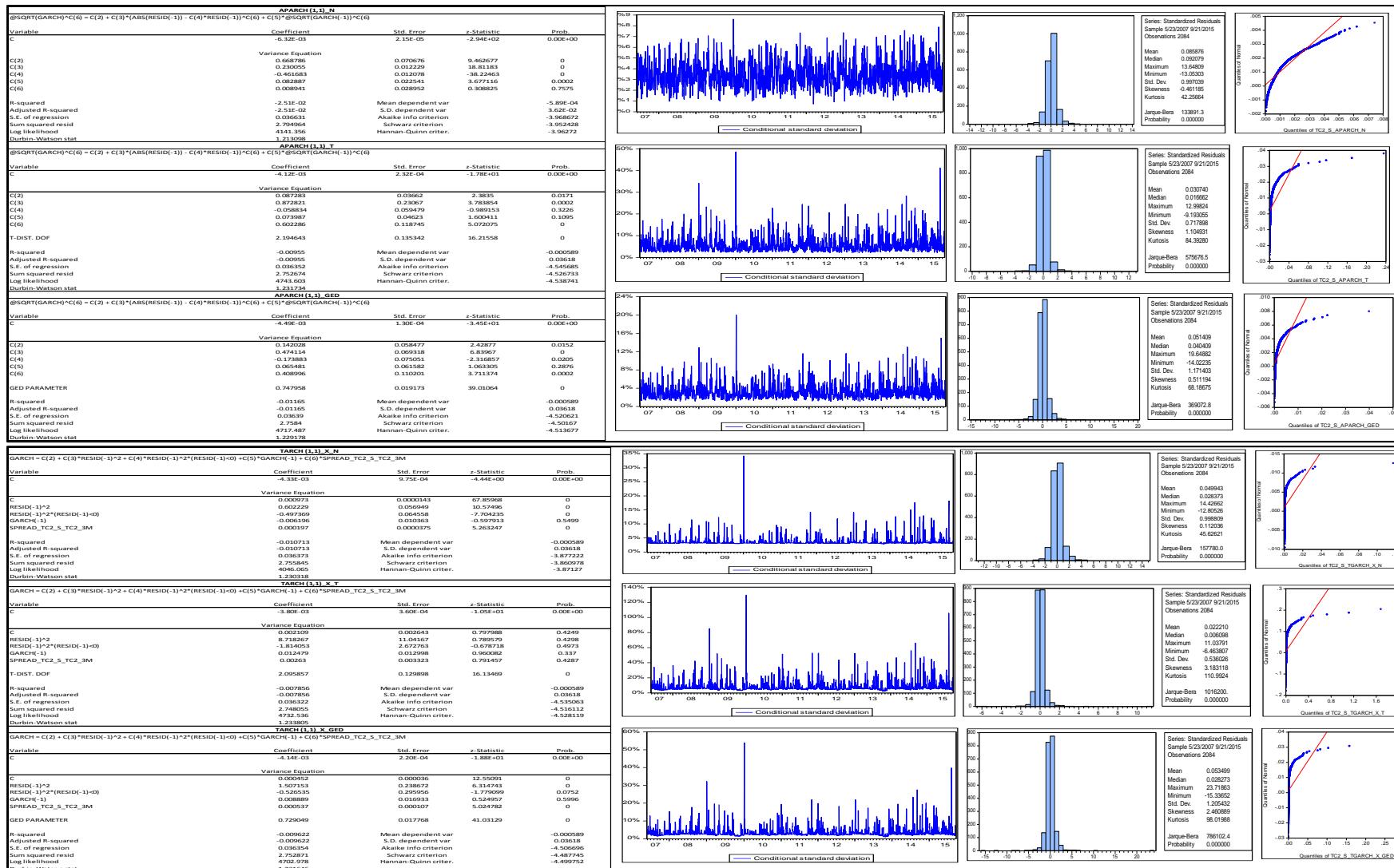
Figure 24: Histograms against the theoretical normal distribution of the returns of spot, 1 Month front and 3 Months front for TD7 route

Appendix B (Eviews)

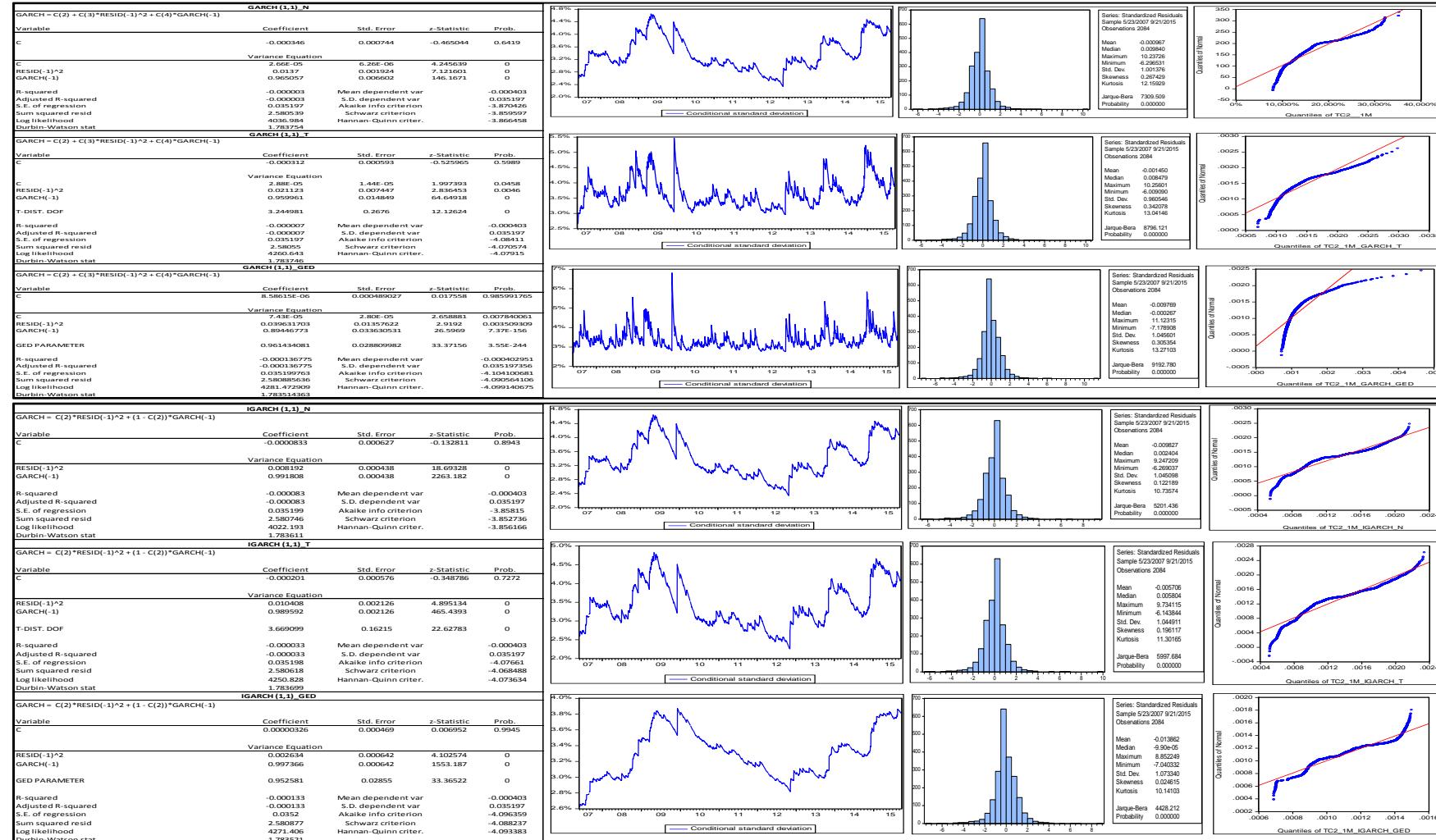
TC2 Spot

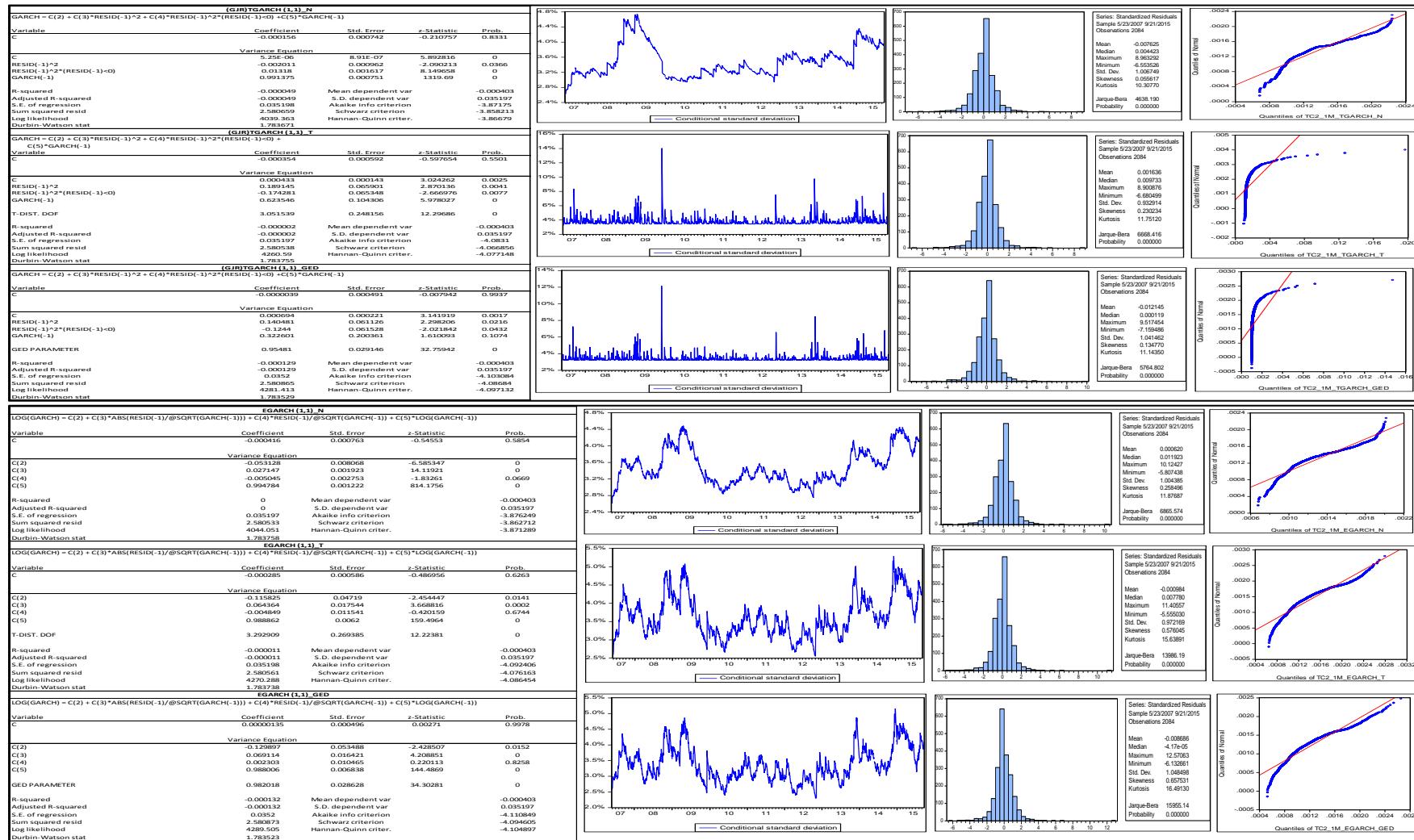


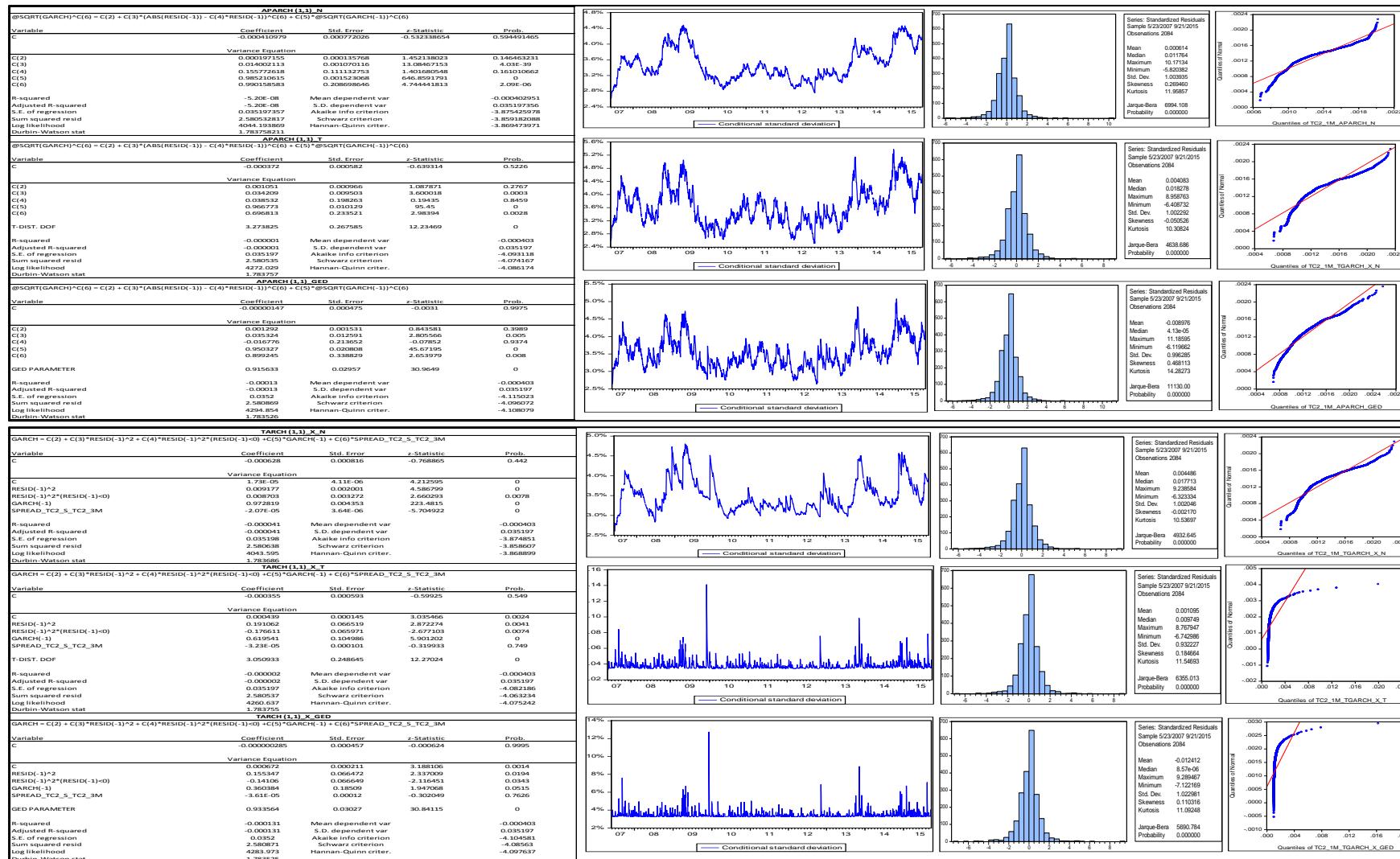




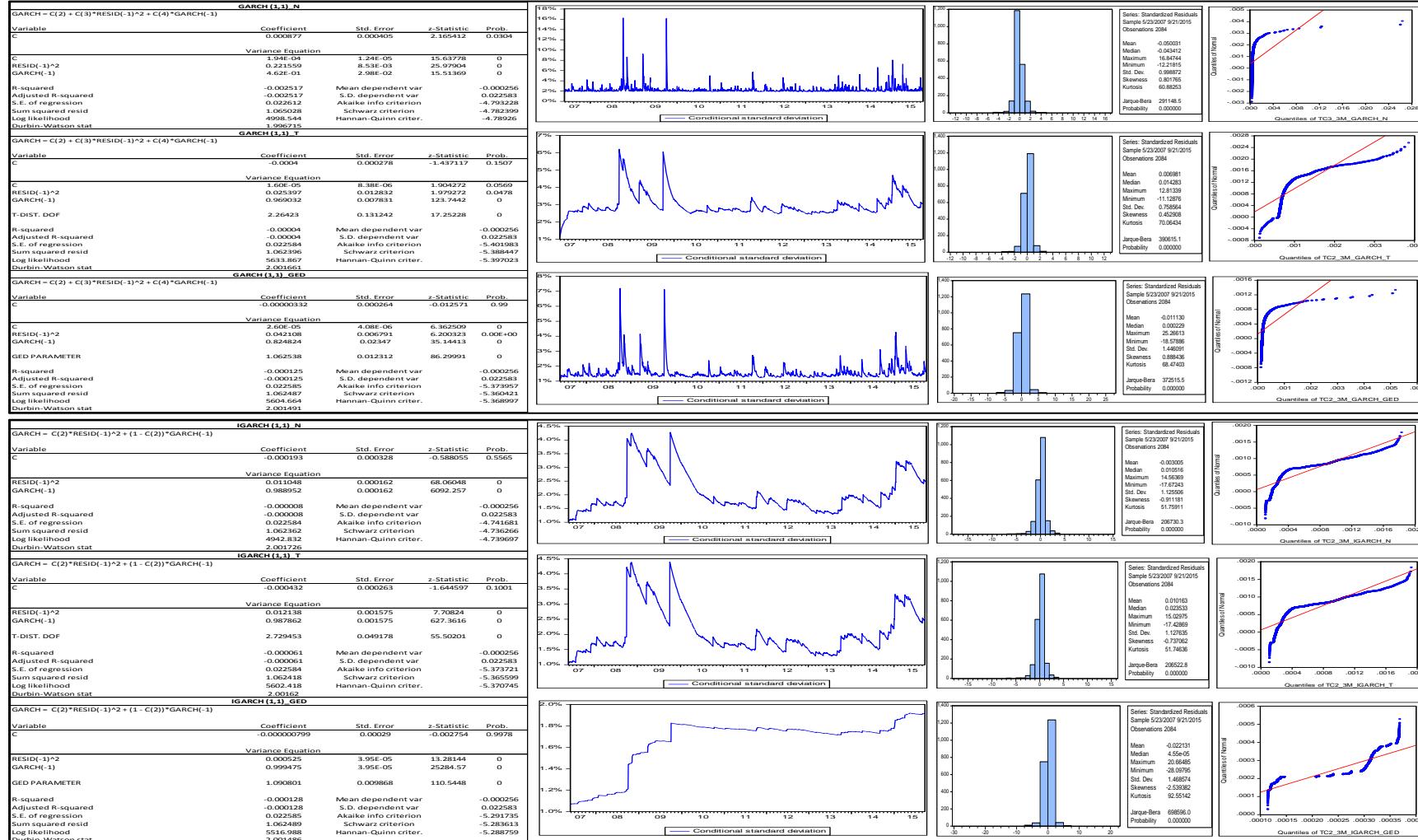
TC2 1 Month Front

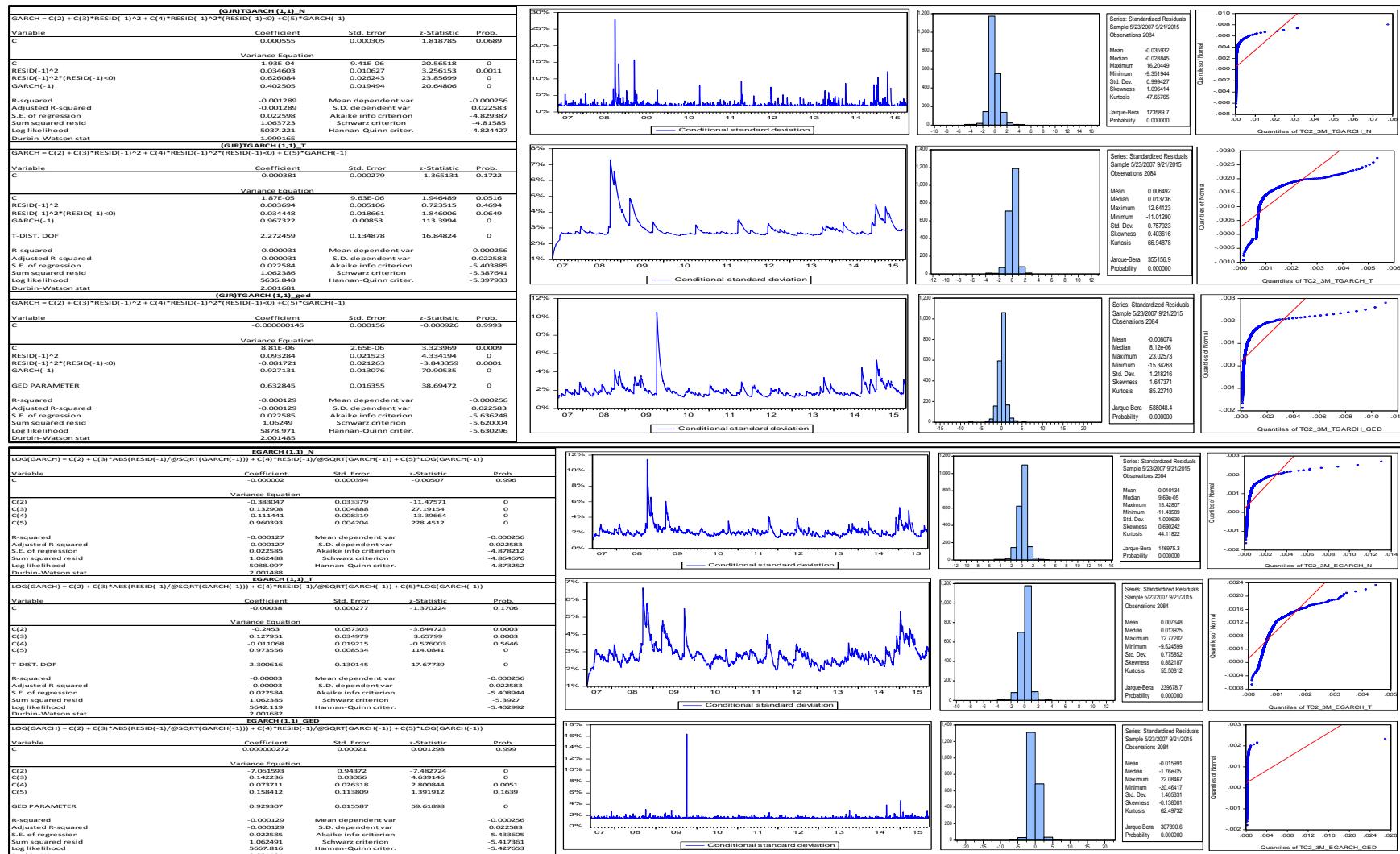


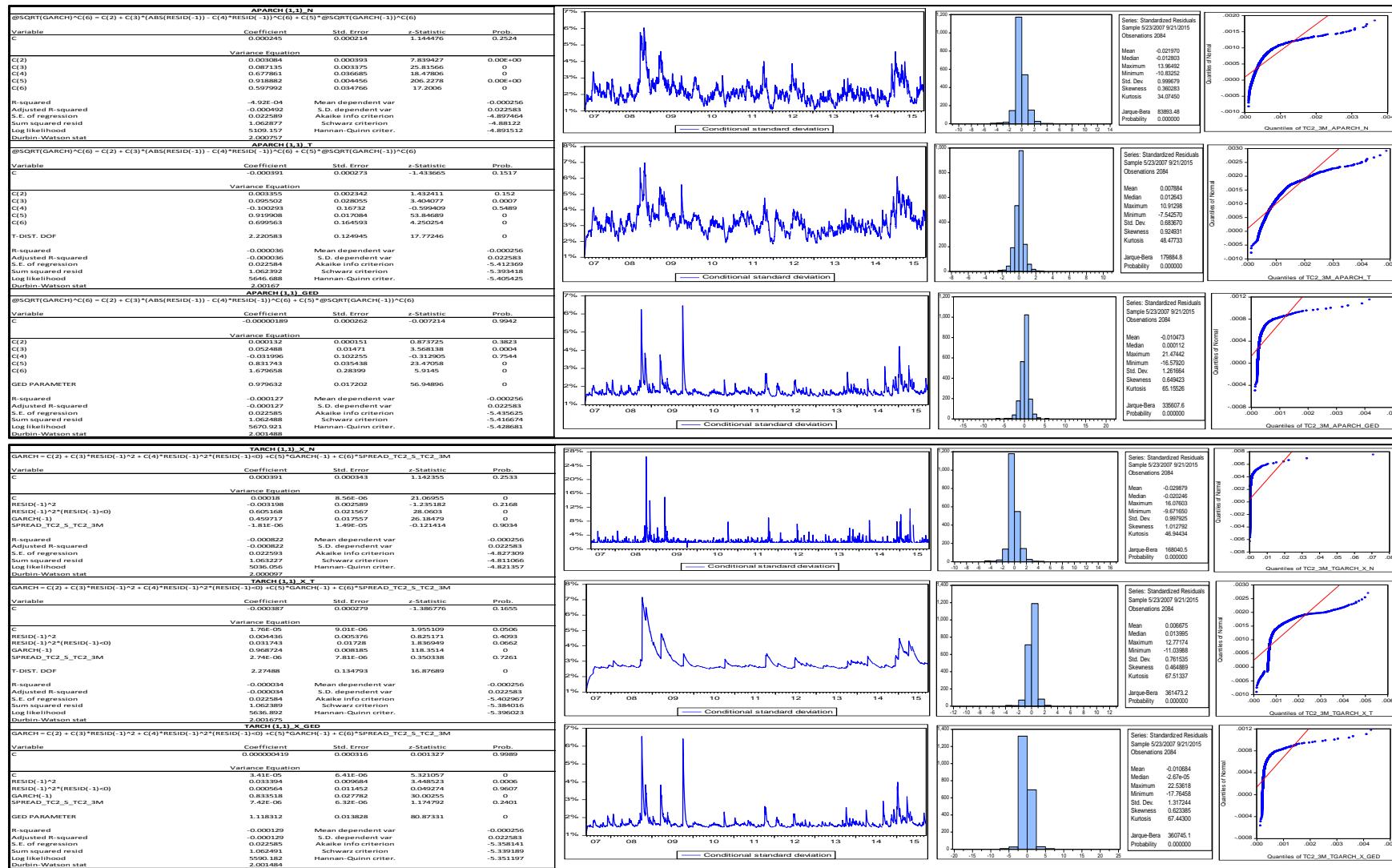




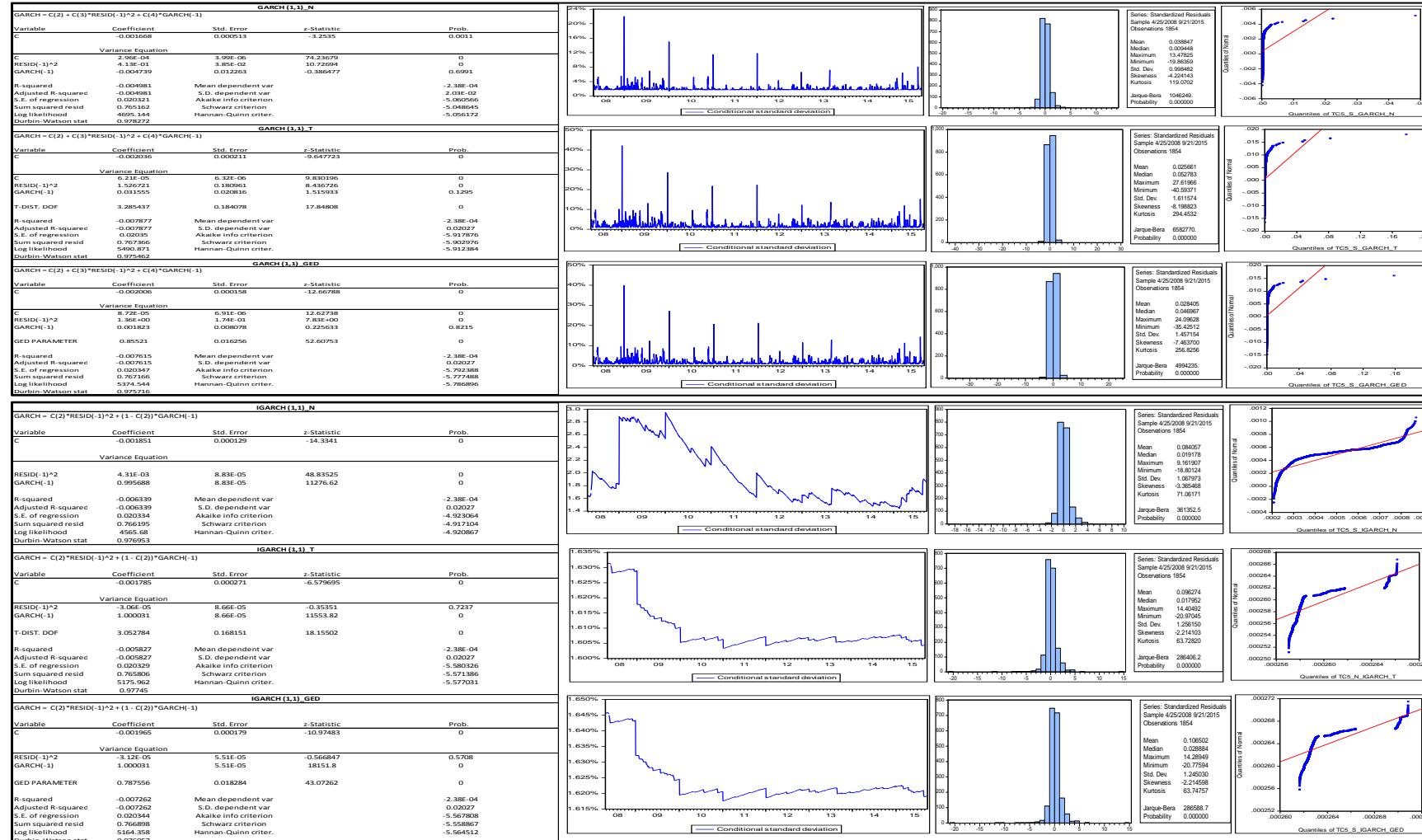
TC2 3 MONTHS

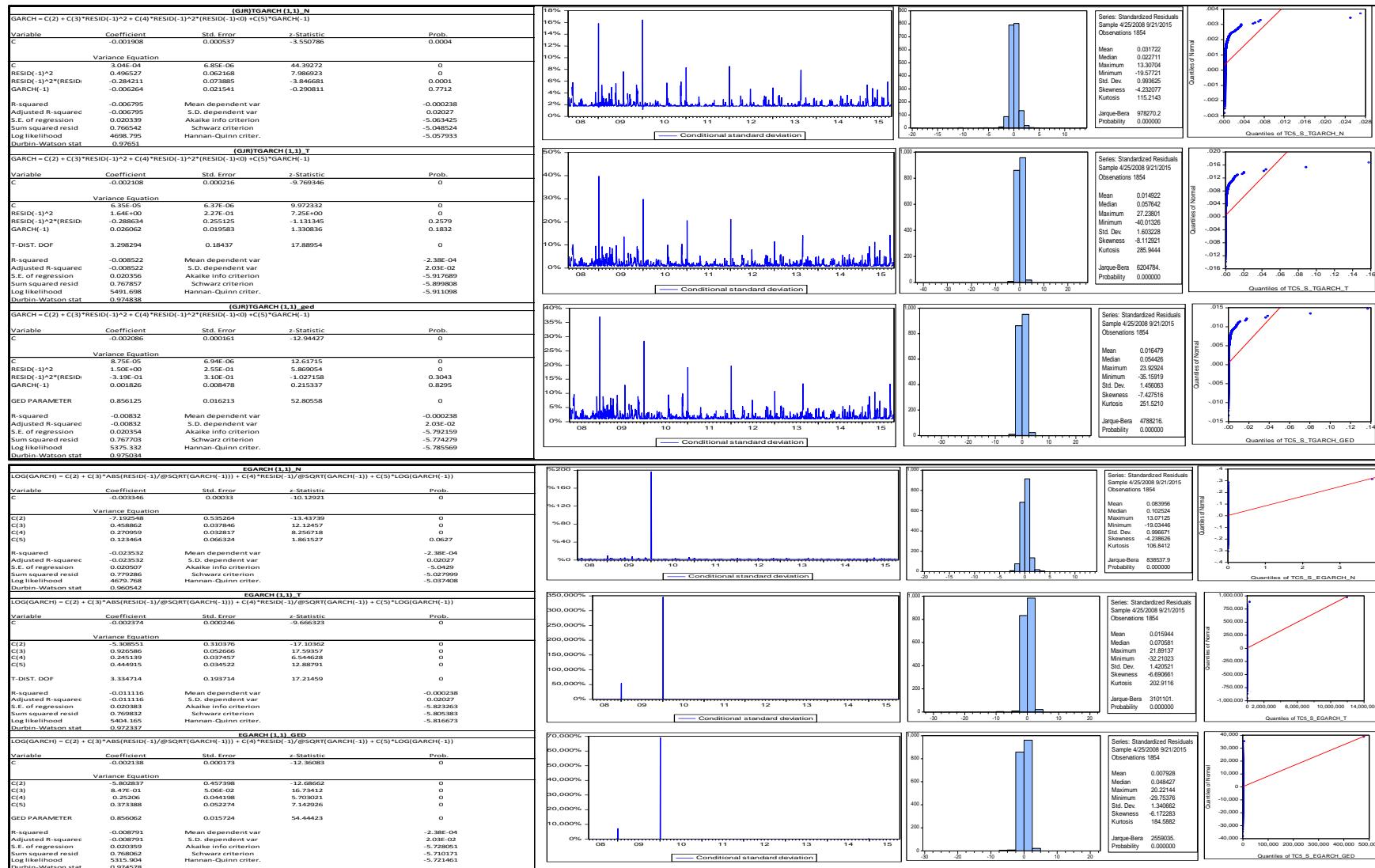


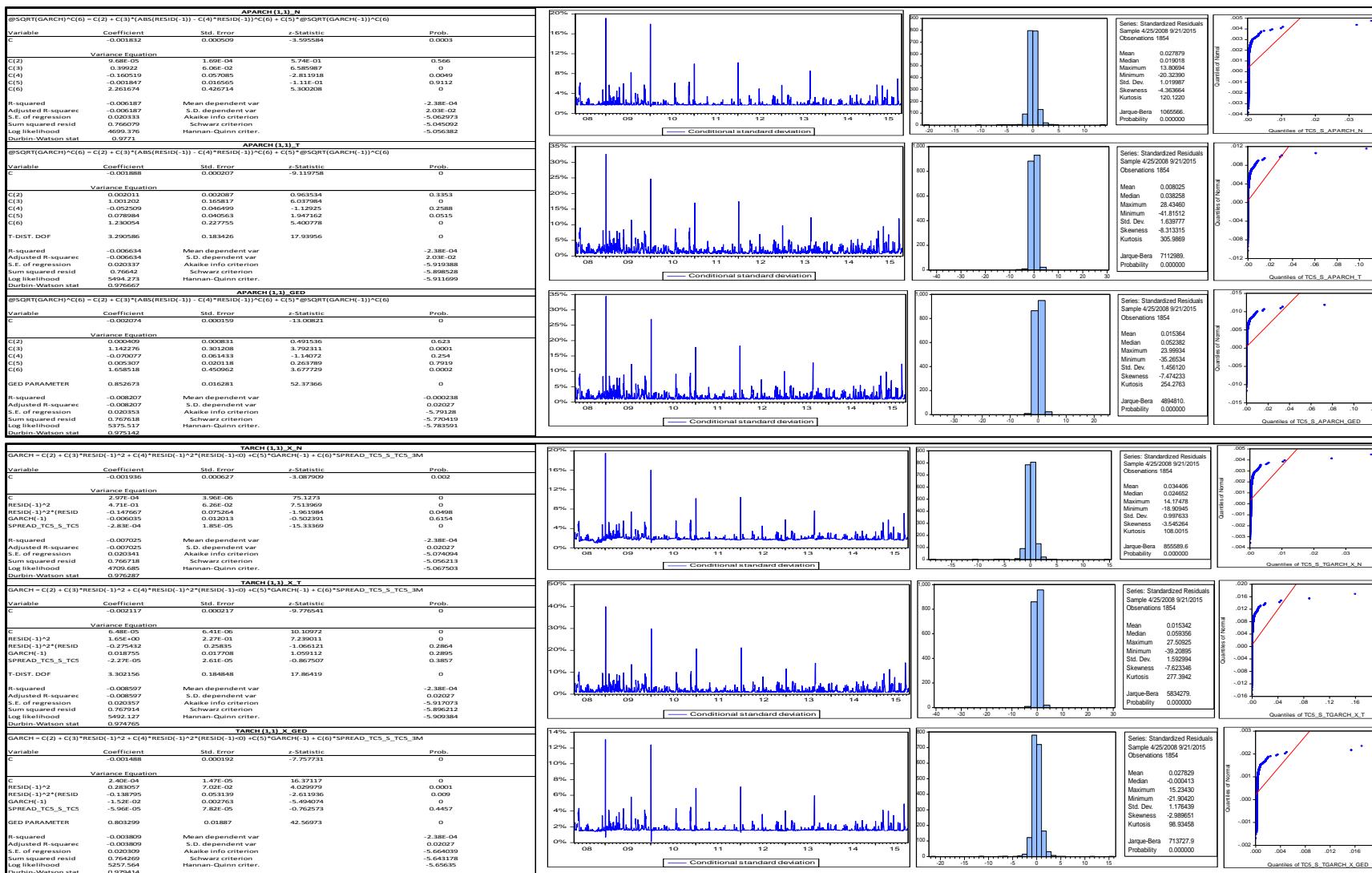




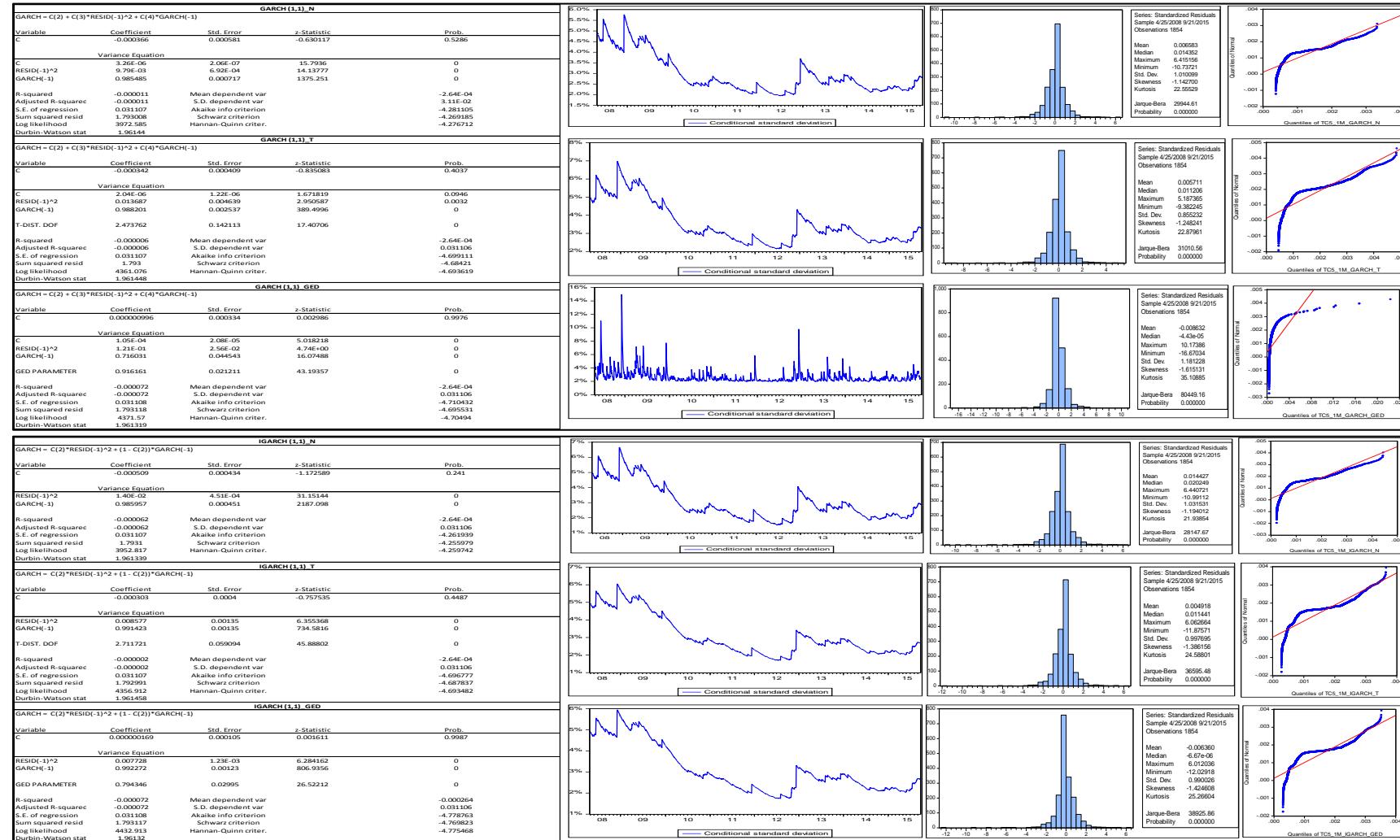
TC5 SPOT

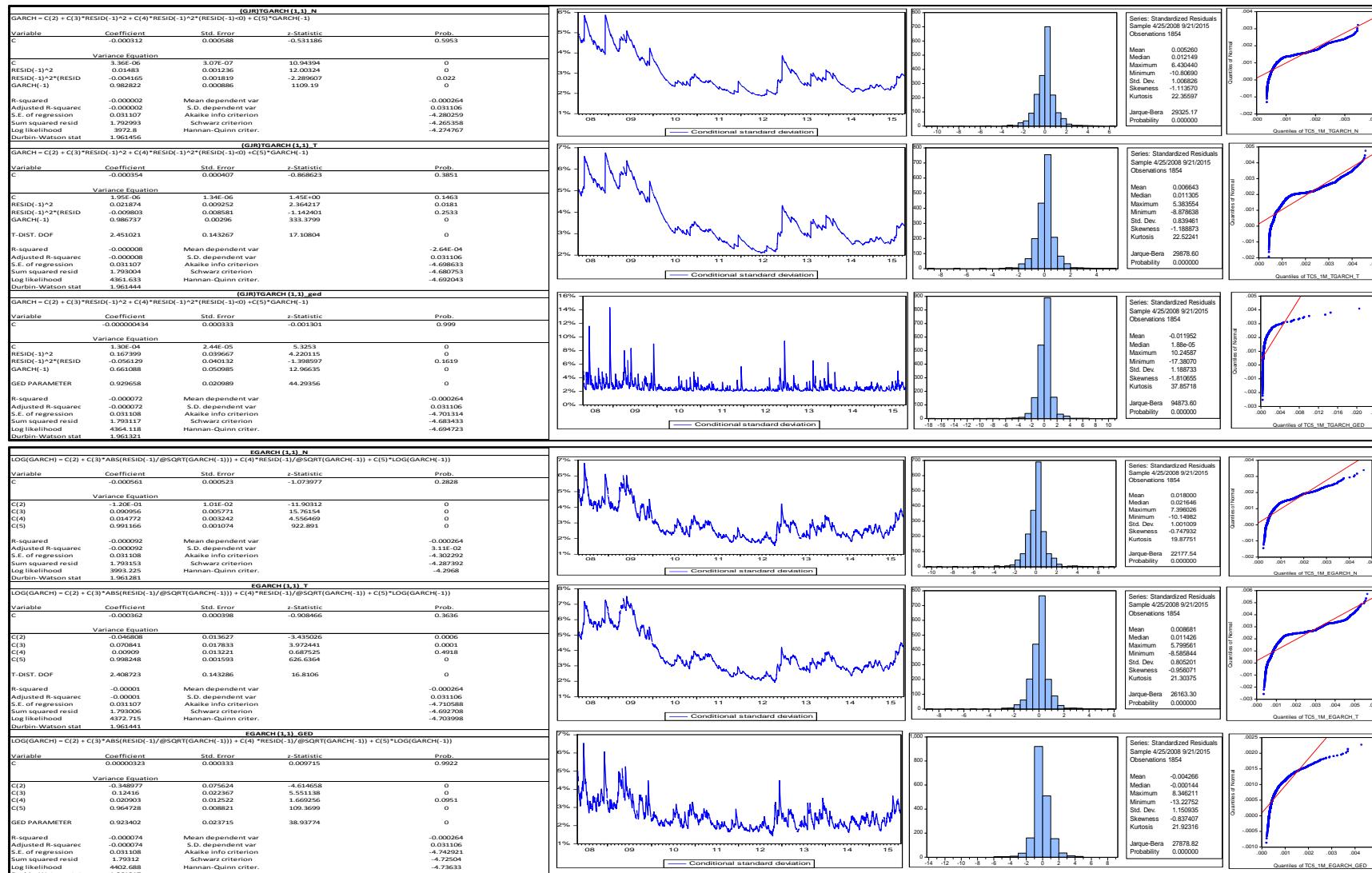


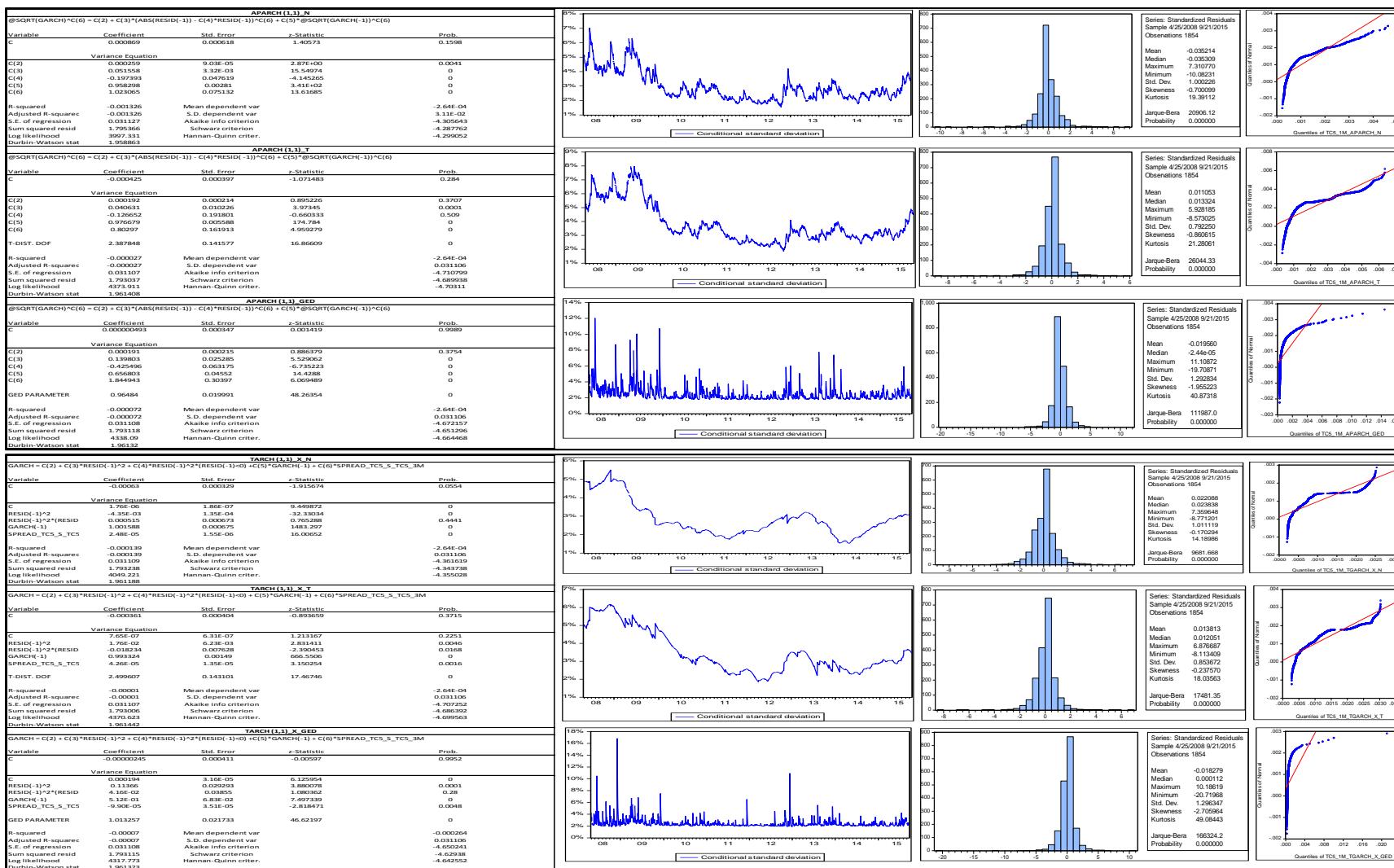




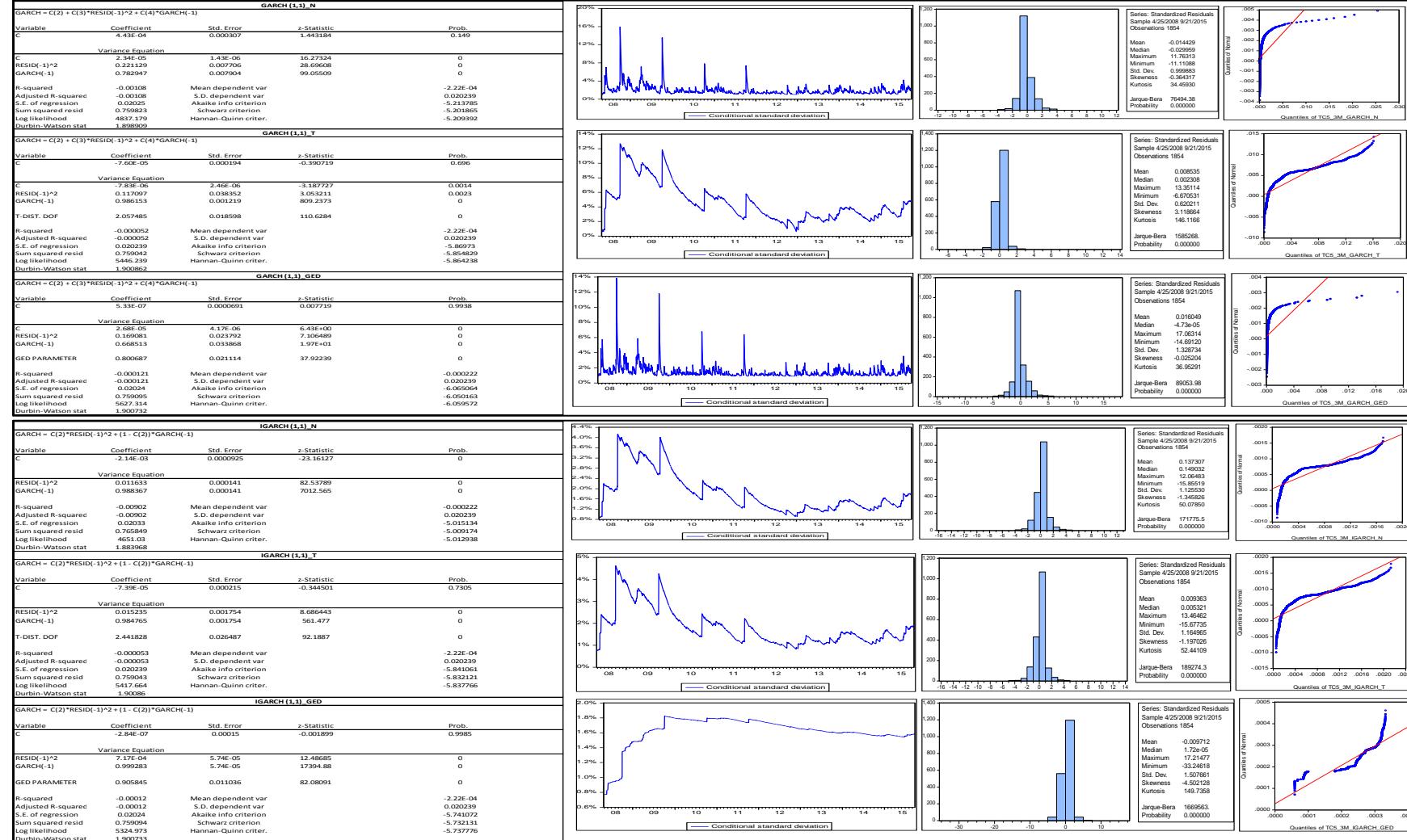
TC5 1 MONTH

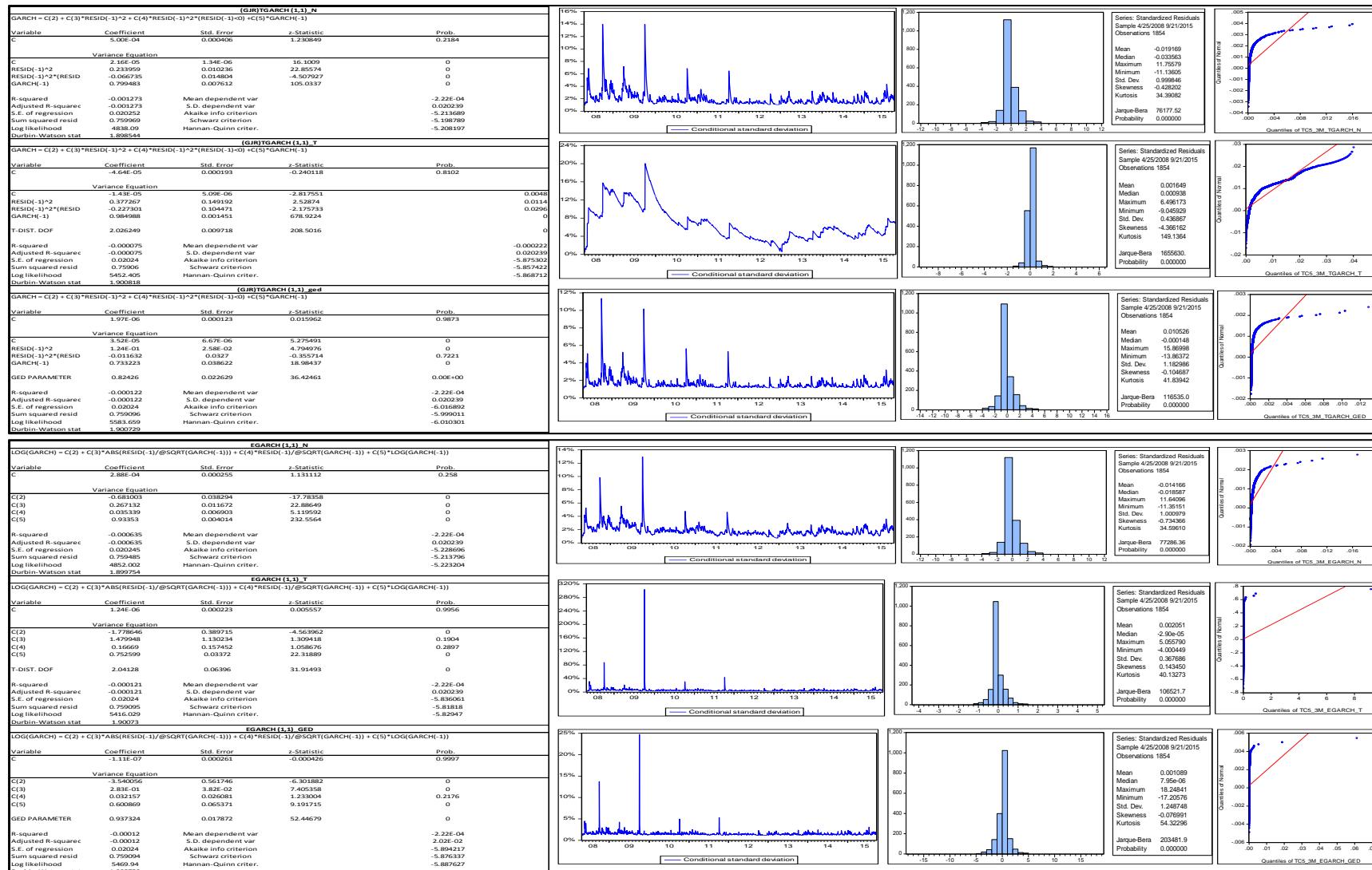


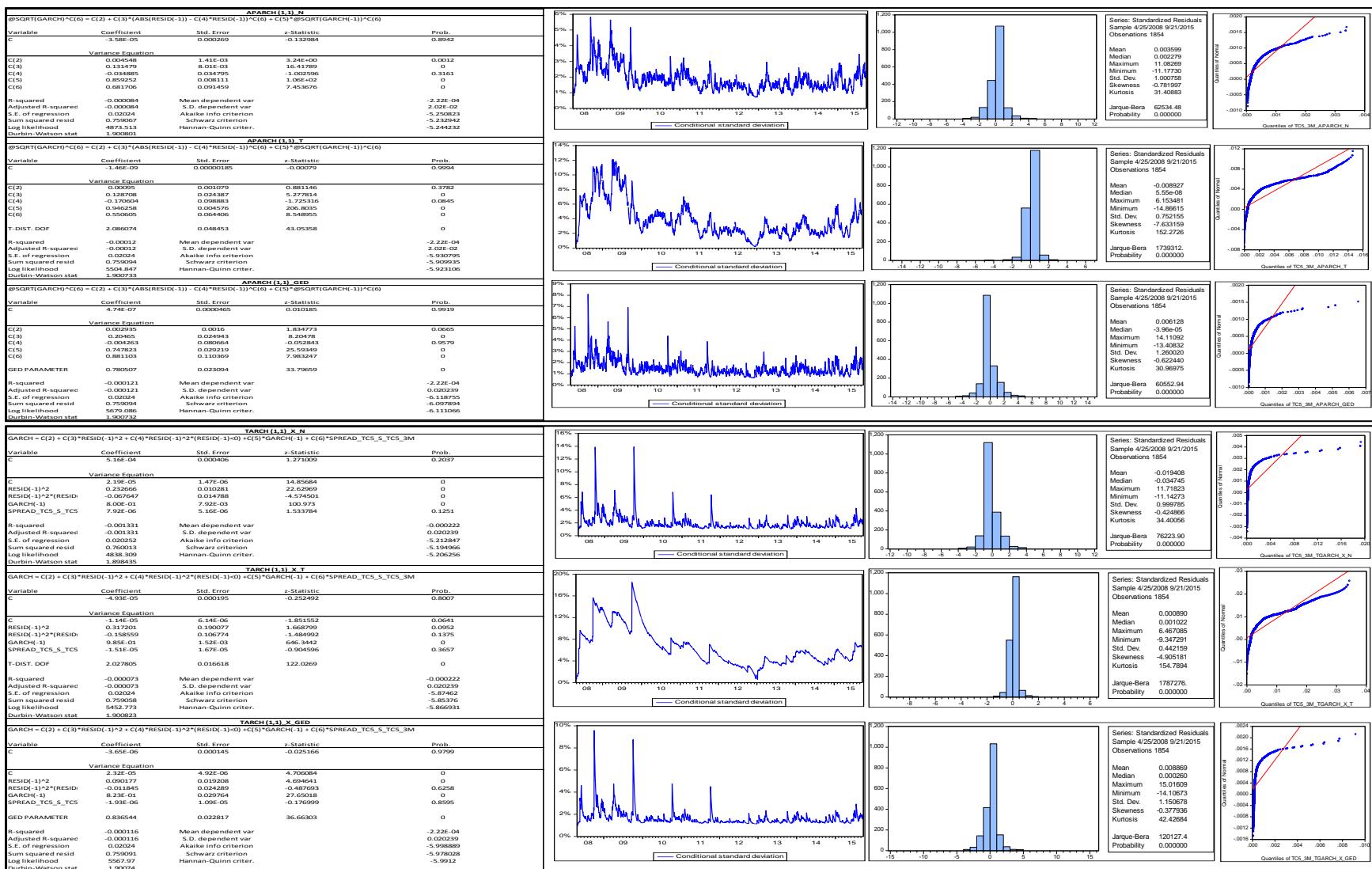




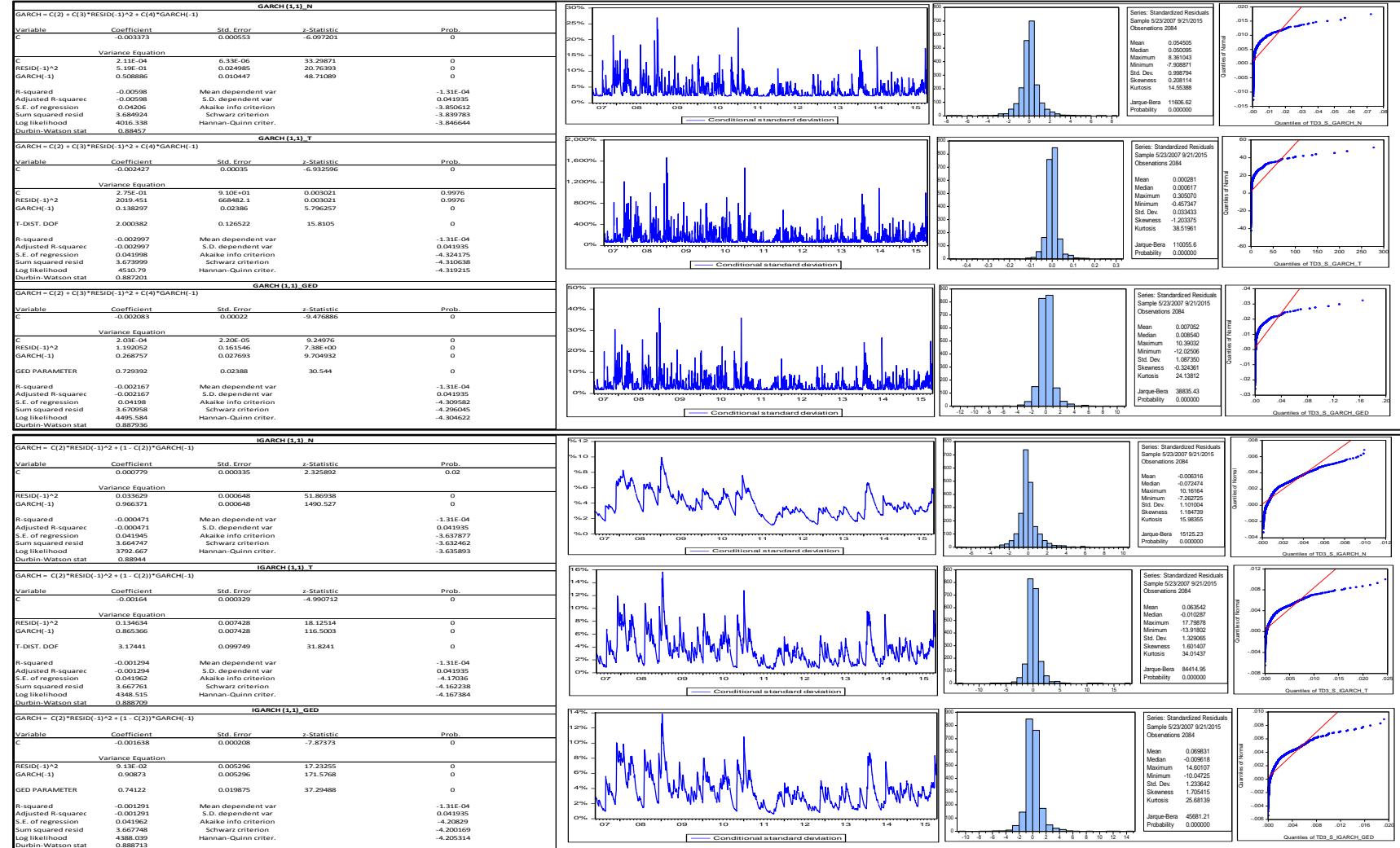
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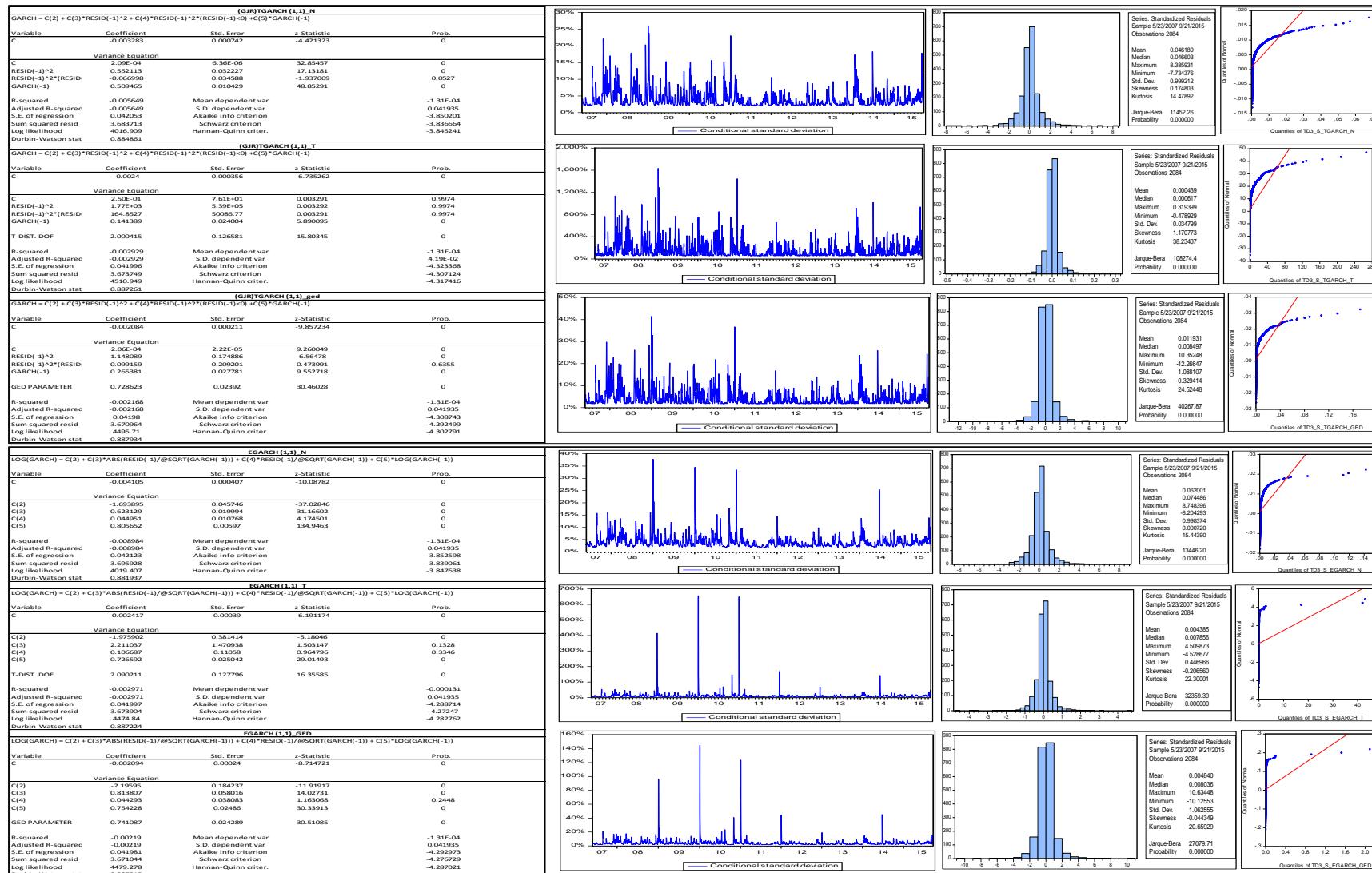


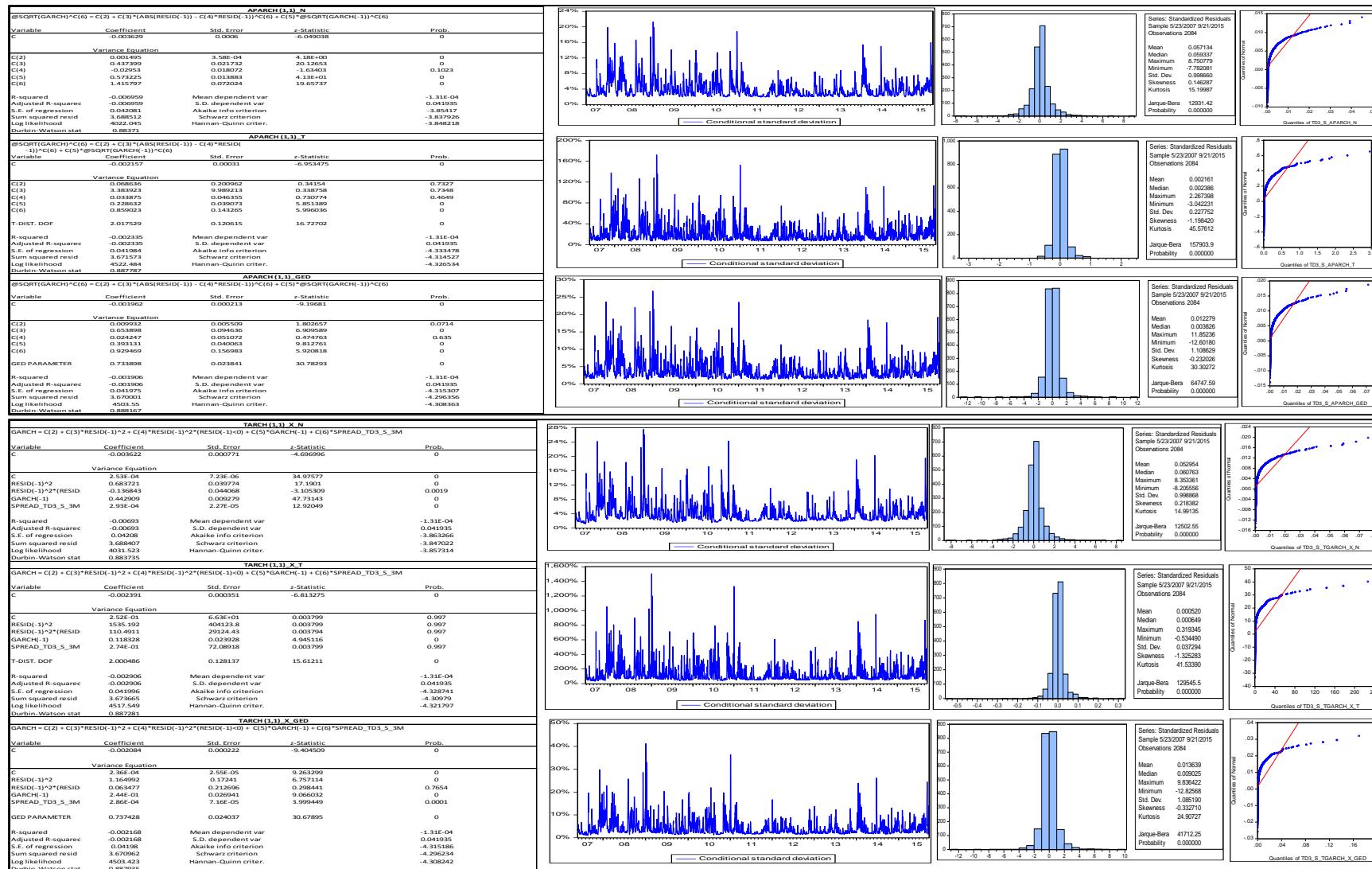




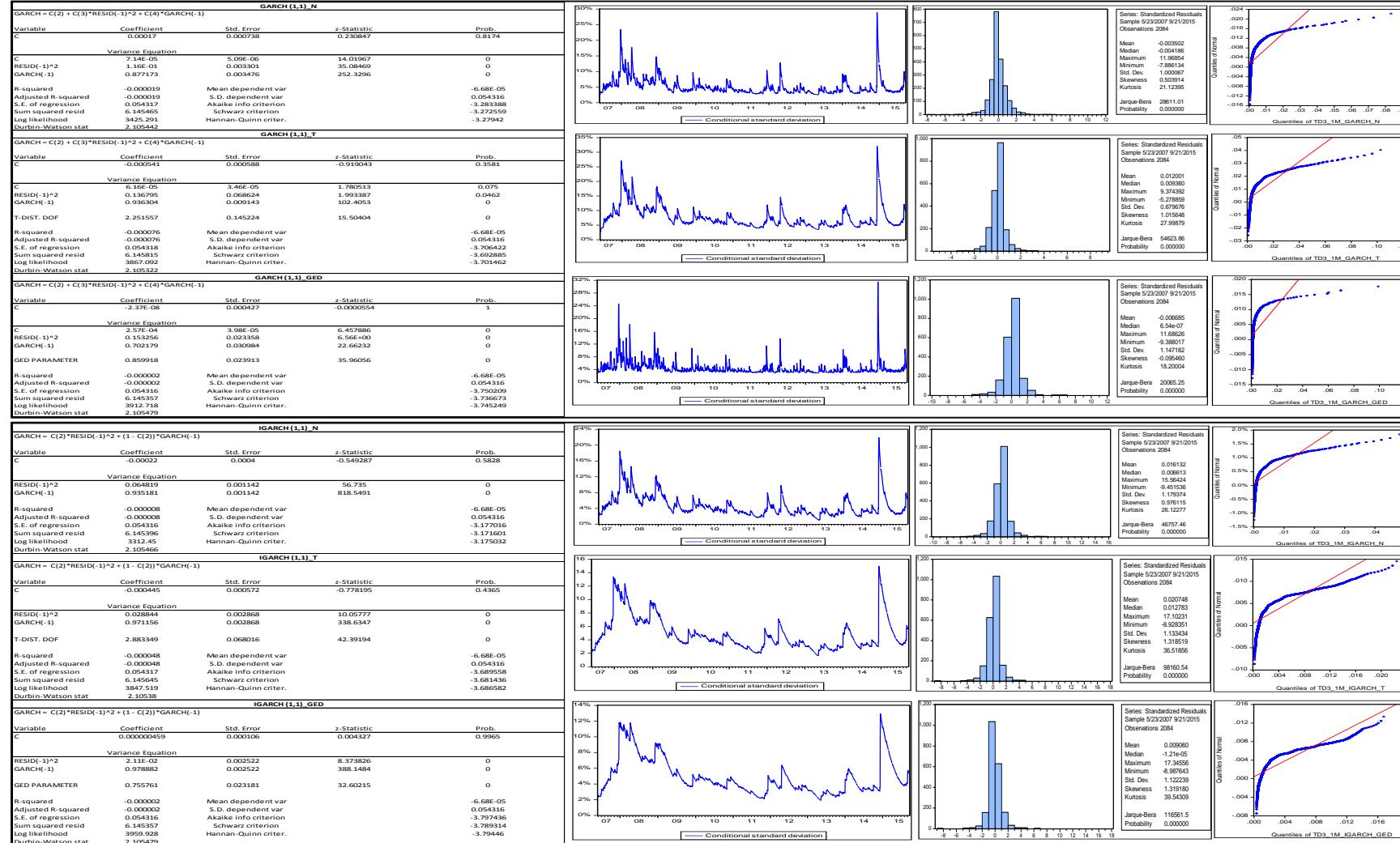
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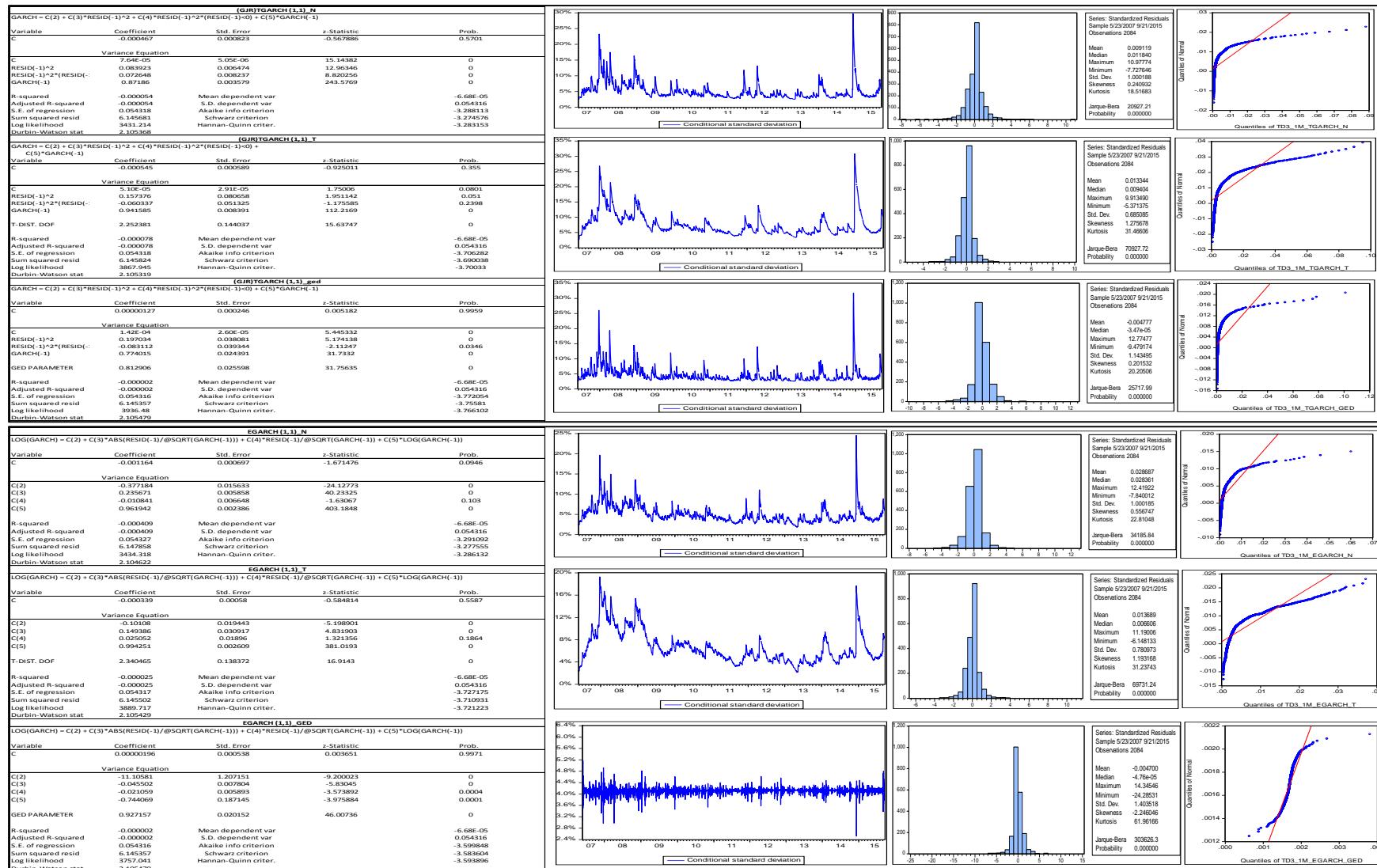


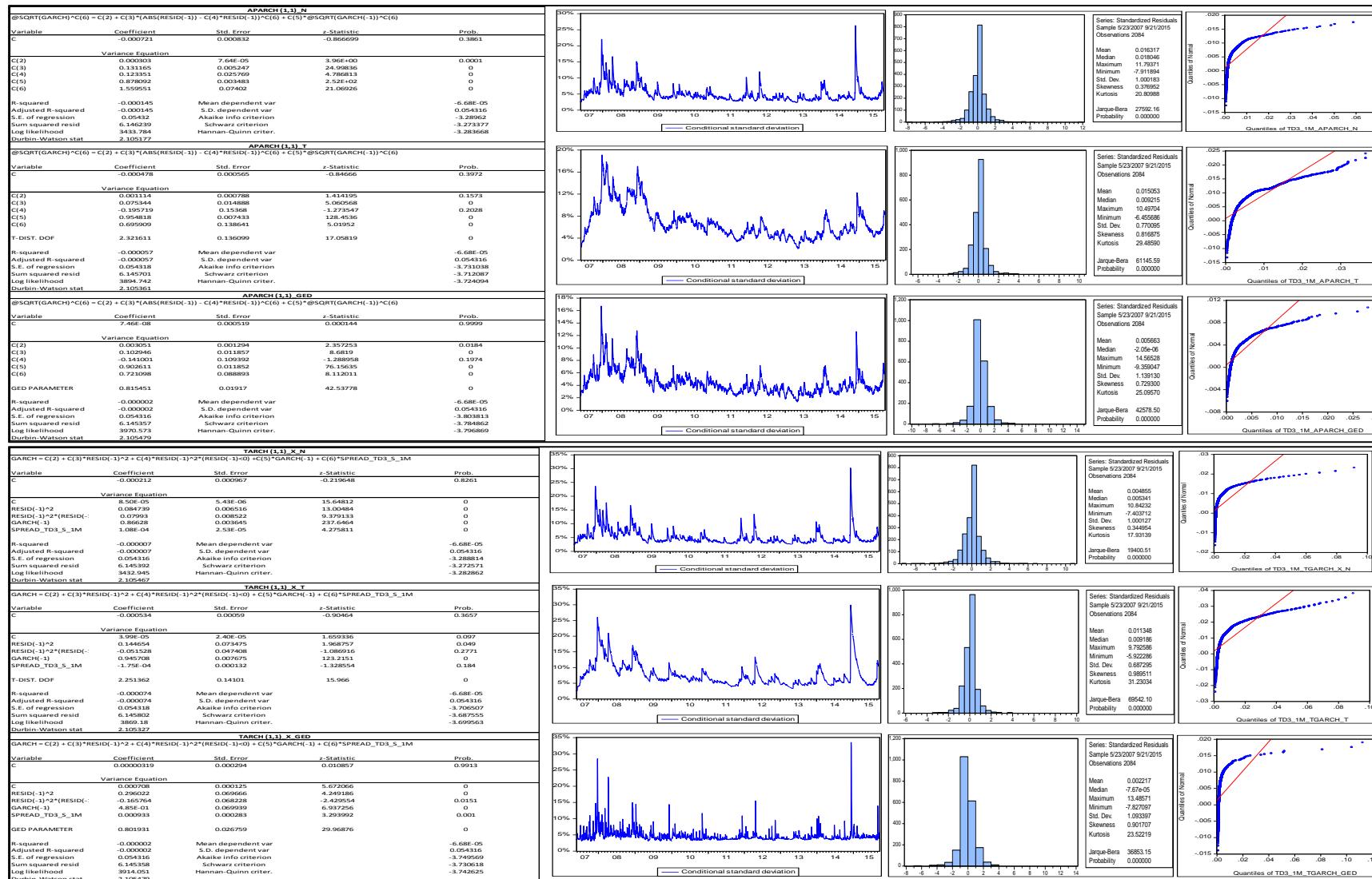




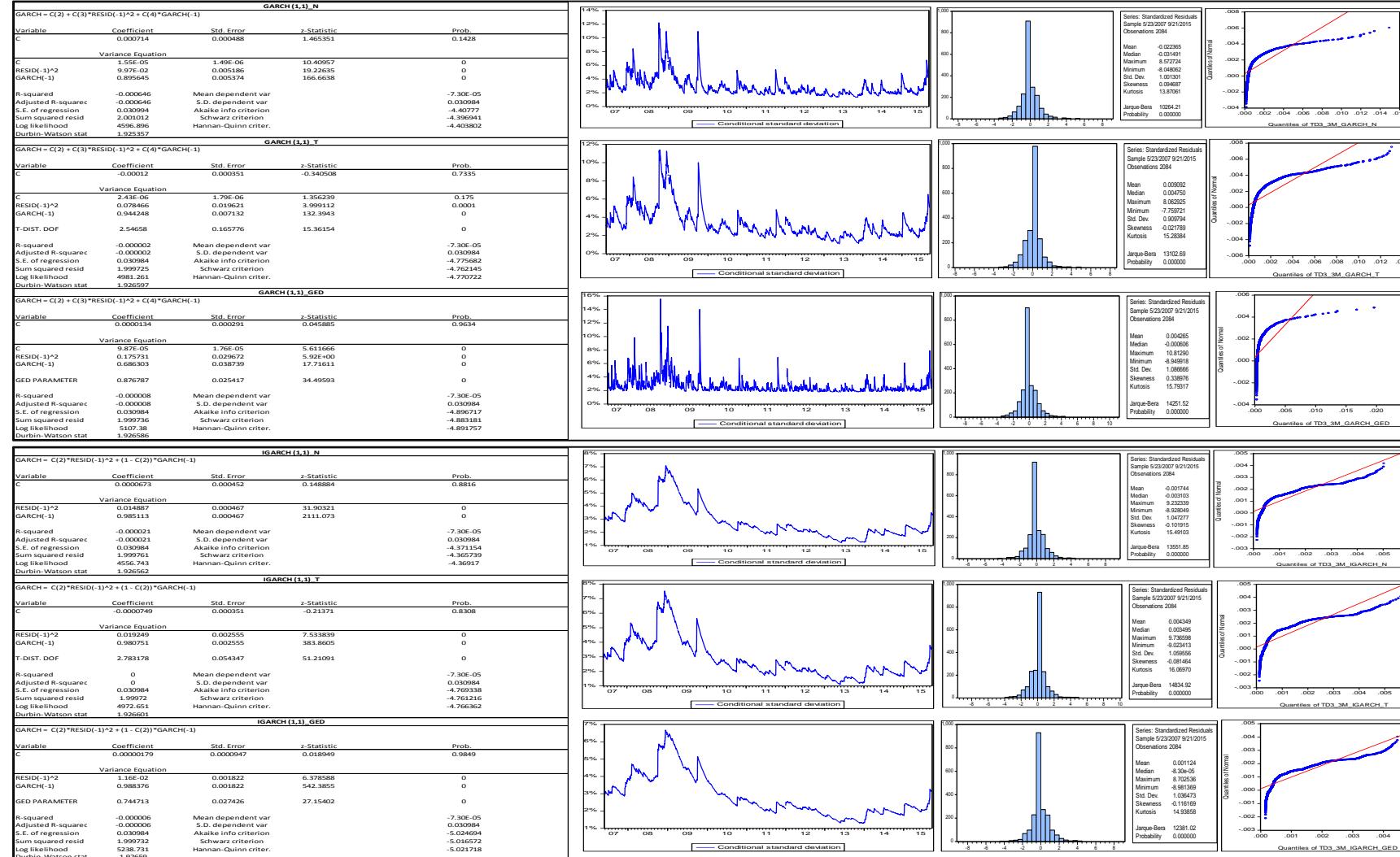
TD3 1 Month

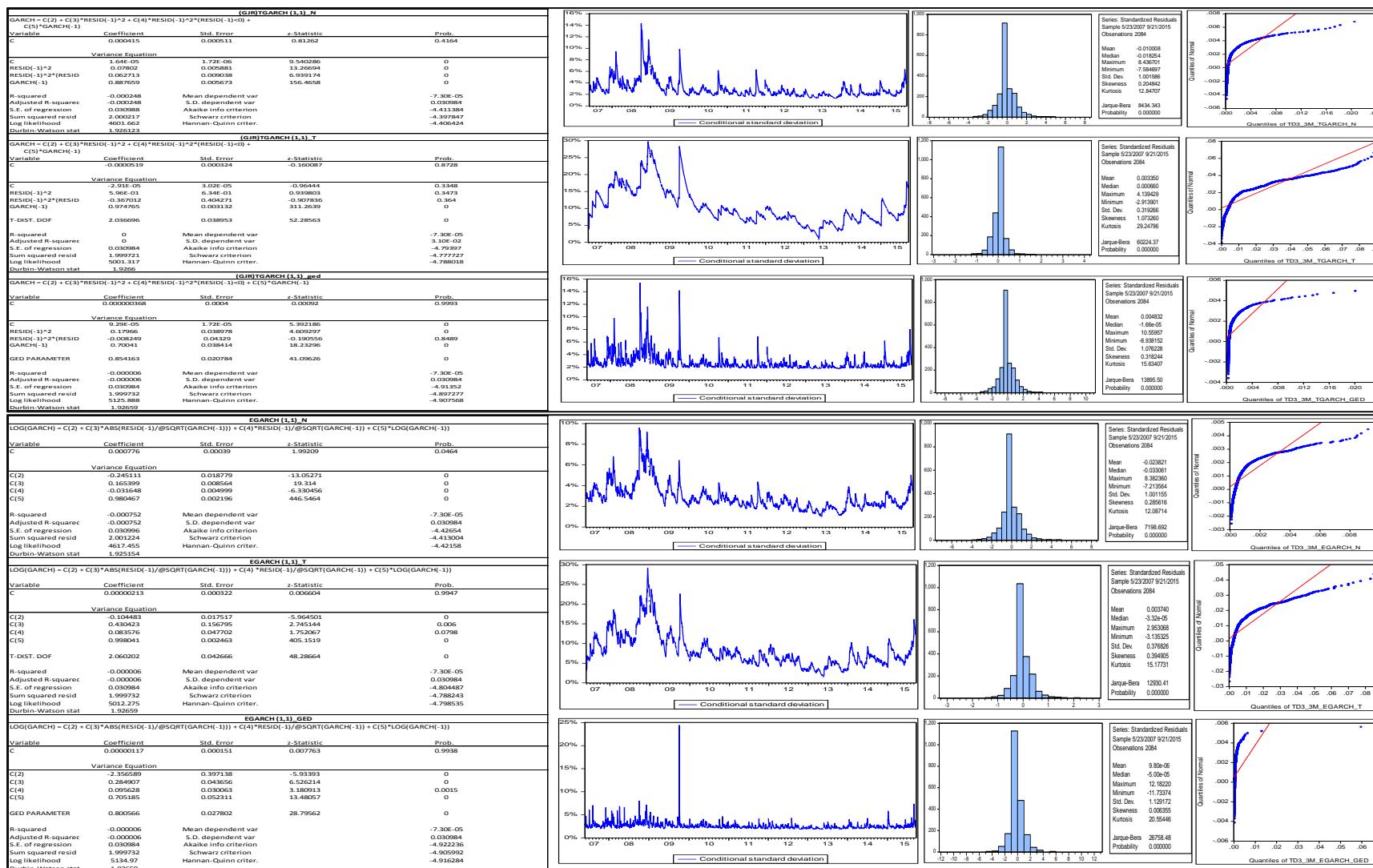


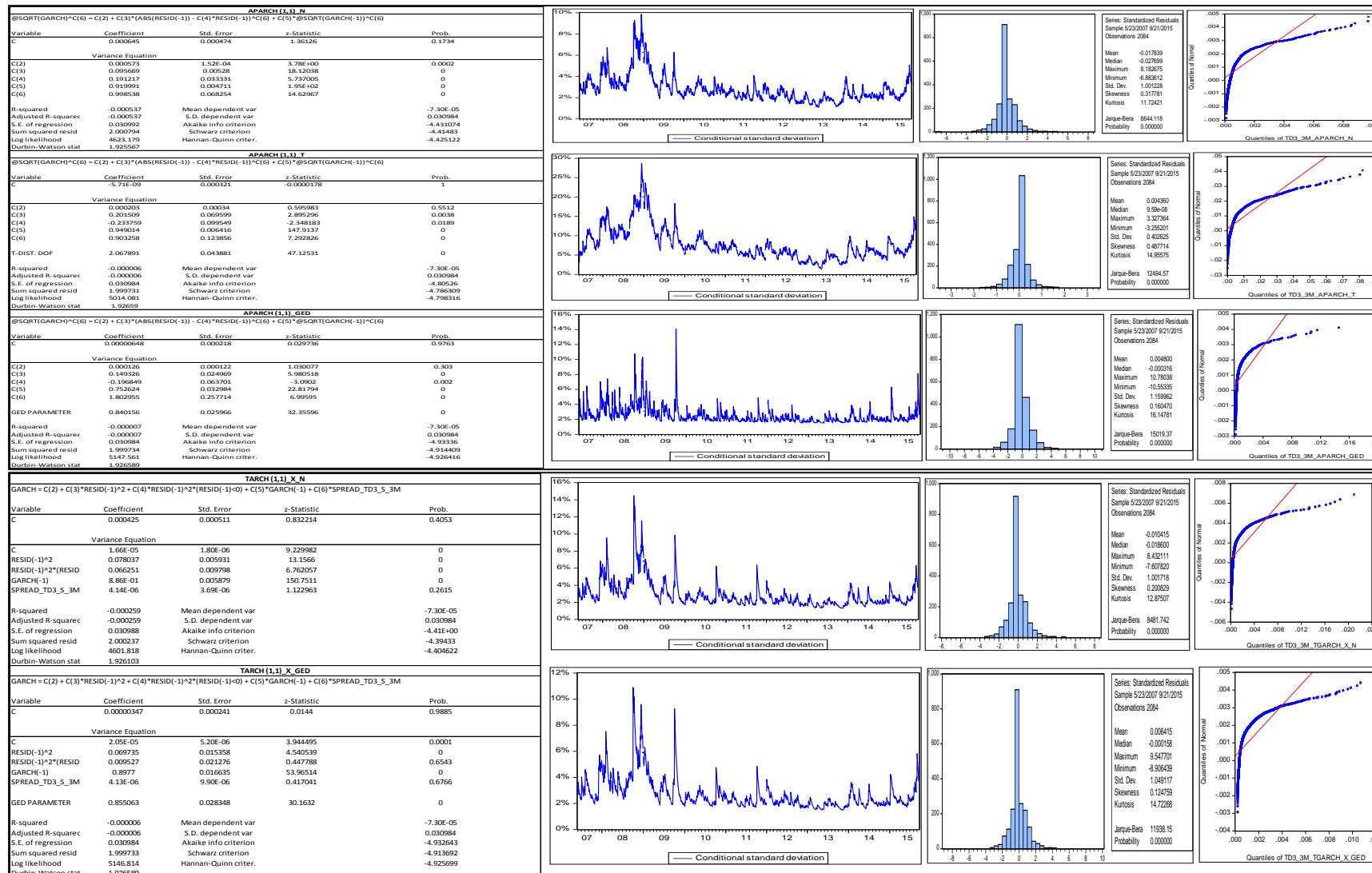




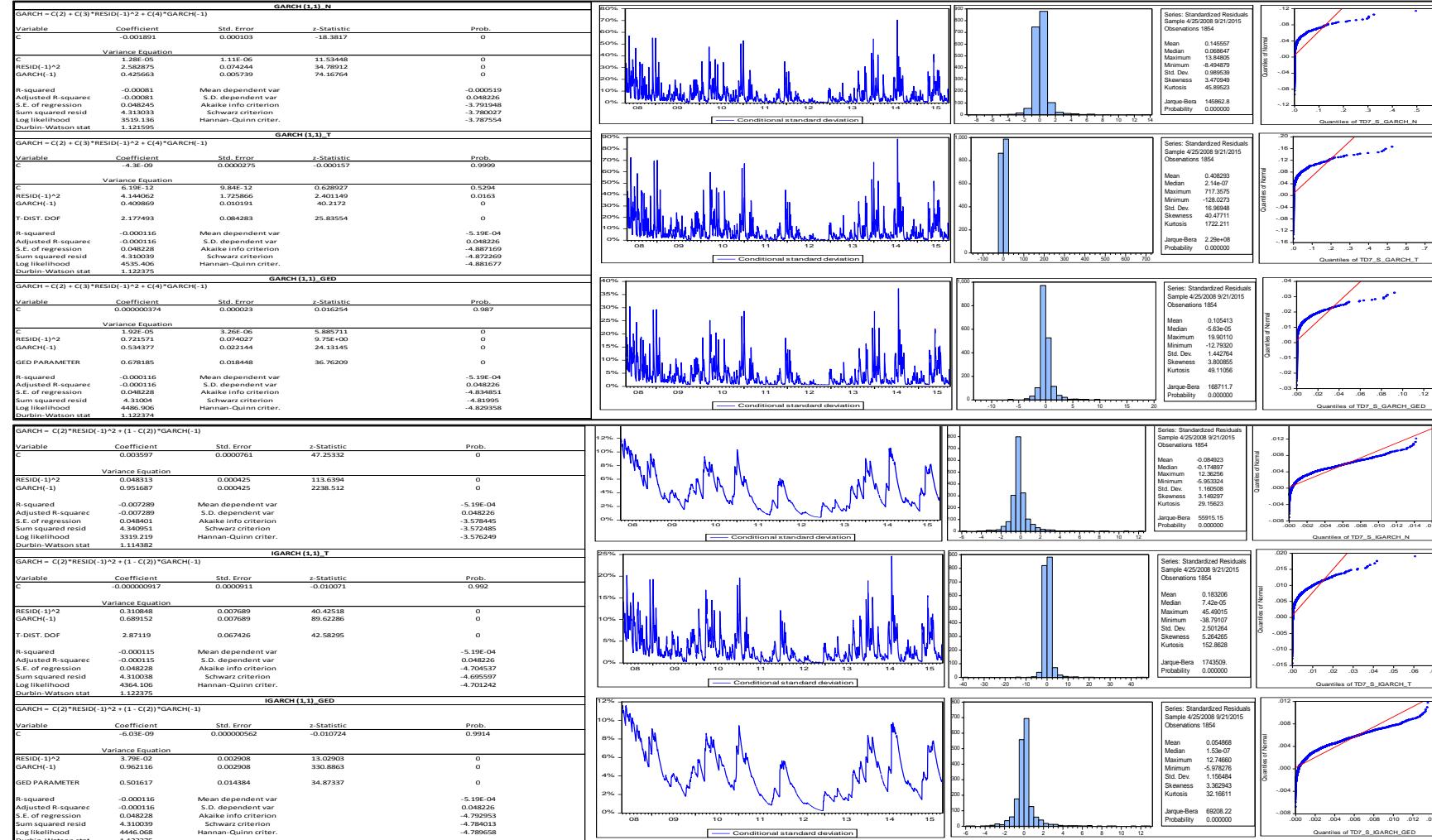
TD3 3 Months

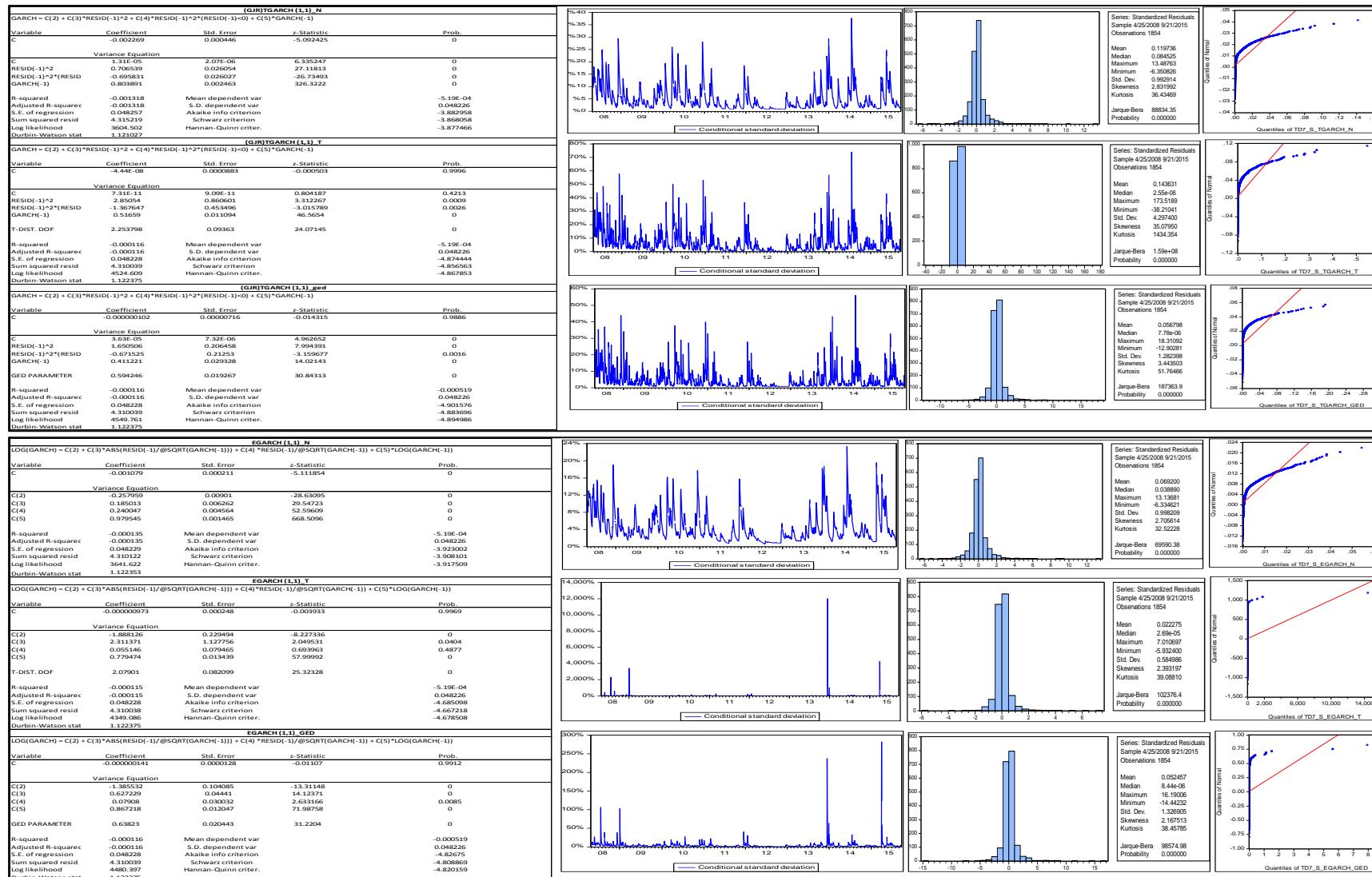


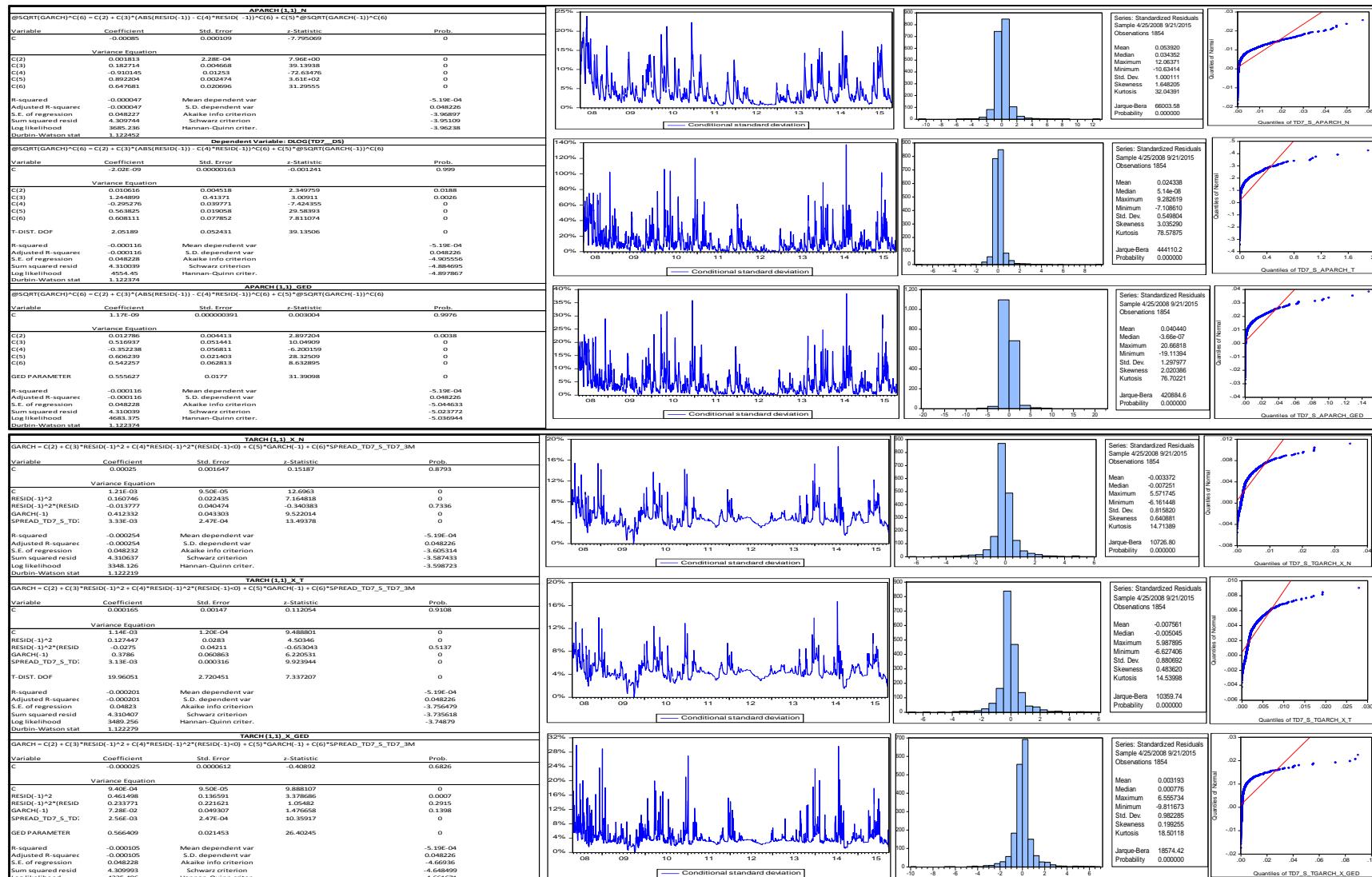




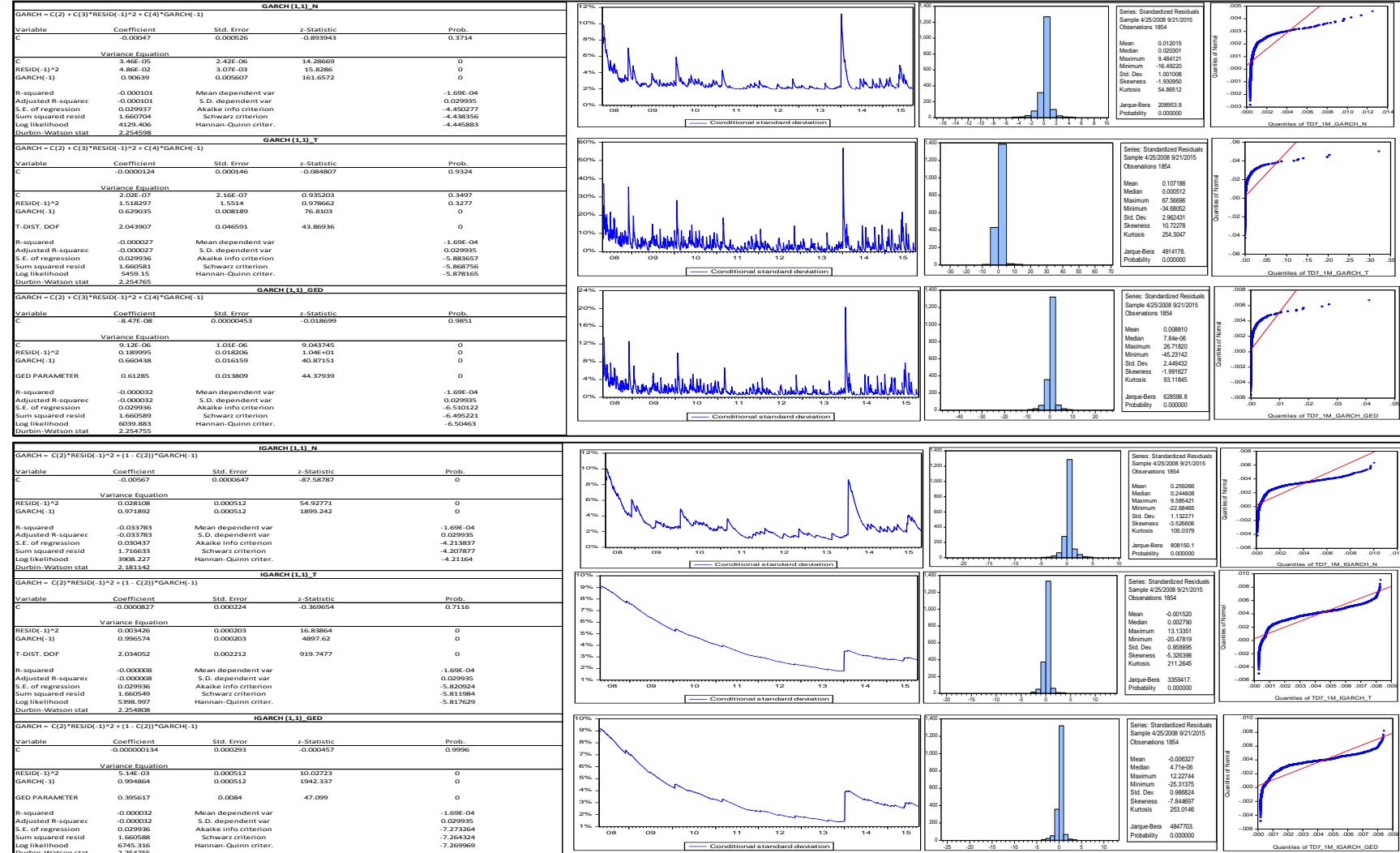
TD7 Spot

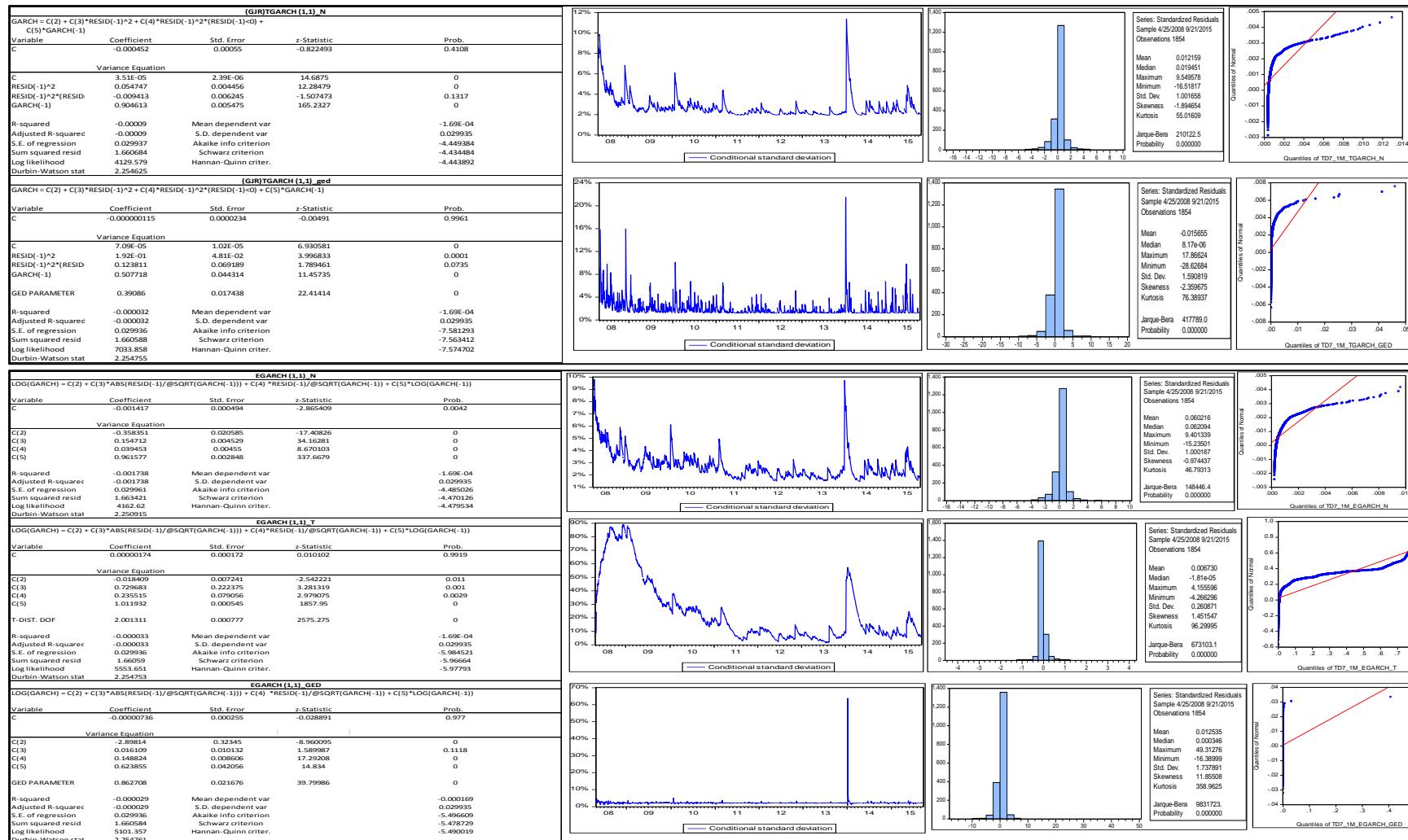


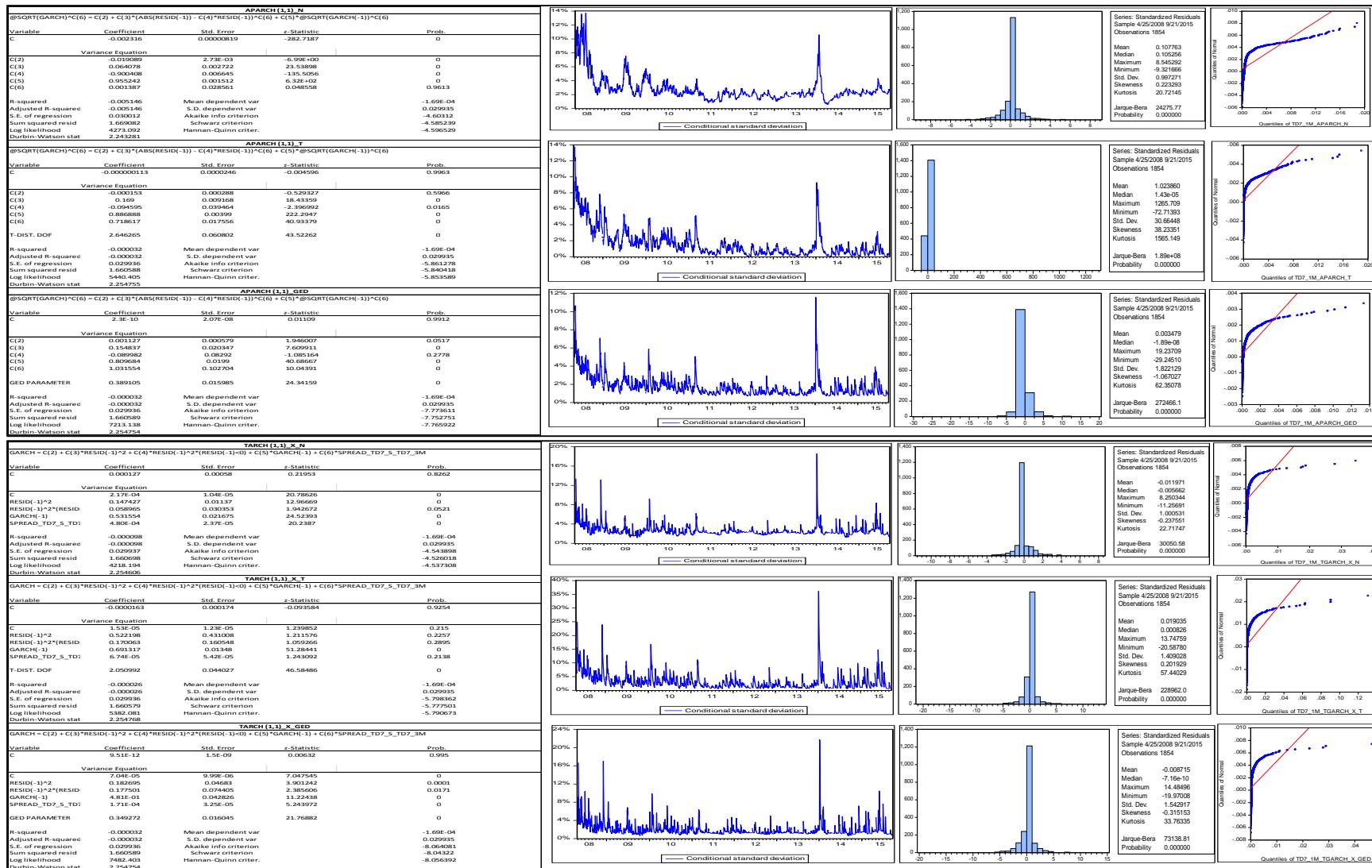




TD7 1 Month







TD7 3Month

