Three Essays on Financial Modelling with Price Limits

by

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I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

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Abstract

In this thesis, a class of clustered censored distributions are proposed in various financial modelling processes. In particular, the proposed distribution can accommodate many stylized (observed) phenomena across different stock markets, especially those with price limits. One main attractive characteristics of the proposed distribution is that it can capture the clustered behaviour of the data over certain continuous interval (while the traditional censored distribution can only allow the clusters to be on the bounds). The clustered censored distribution is developed and presented, to some extent, in a general way so that it can be transformed into other well-known distributions, such as the classical Normal distribution, one- (or two-) sided truncated distribution, one- (or two-) sided censored distribution, etc. The clustered censored distribution is further designed into some well-known financial modelling structures, such as Generalized Autoregressive Conditional Heteroskedasticity ($GARCH$, Bollerslev (1986)) process. We also investigate the potential applications of the proposed models in this thesis to risk management.

Overall, there are three main chapters in the thesis. Chapter 1 introduces the fundamental theory and properties of the proposed clustered censored distribution. As a starting point, Normality is mainly considered in this chapter. Built on Chapter 1, Chapter 2 designs a $GARCH$ process with the cluster censored Normal distribution (referred as $GARCHCCN$). The model performance is investigated via Monte Carlo experiments and empirical data. The risk implication is also discussed in Chapter 2. Chapter 3 consists of two dimensions of the extensions. Sections 3.1-3.4 extend the model using clustered censored heavy tailed distributions, such as Student-t and Generalized Error Distribution (GED), for a better performance in capturing the tail behaviour. Section 3.5 examines the dynamic spillover effects under the proposed model framework. There are 14 supporting appendices (A-N) mainly for proofs, tables and figures.

Keywords

price limits, clusters, fat tails, Monte Carlo simulations, truncated normal, truncated $GARCH$, censored normal, censored $GARCH$, clustered censored normal, clustered censored $GARCH$, Student's t-distribution, Generalized Error Distribution/GED, $VaRs$, $Kupiec$ LR test, $Christoffersen's$ test, spillover effects, in-sample, out-of-sample, moment simulations, probability density function, cumulative density function

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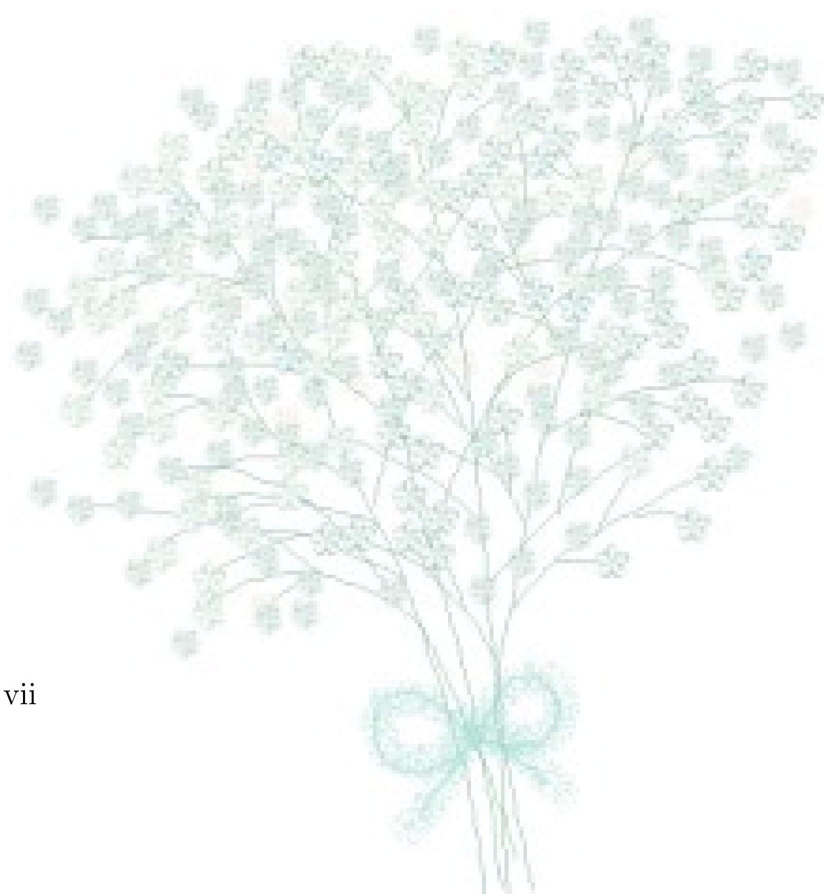
This thesis is dedicated to my parents, my daughter, and my son.
For their endless love



Motivational Quotes

"The most difficult thing is the decision to act, the rest is merely tenacity."

Amelia Earhart

"Apply yourself. Get all the education you can, but then, by God, do something. Don't just stand there, make it happen."

Lee Iacocca

Table of Contents

List of Tables

List of Figures

Abbreviations

AIC . . . . . . the **A**kaike **I**nformation **C**riterion
BIC . . . . . . the **B**ayesian **I**nformation **C**riterion
CAC . . . . . **C**otation **A**ssistée en **C**ontinu
cdf . . . . . . **c**umulative **d**ensity **f**unction
GMM . . . . **G**eneralized **M**ethod of **M**oments
KOSPI . . . . **K**orea **C**omposite **S**tock **P**rice **I**ndex
LOGL . . . . **LOG**-**L**ikelihood
Lower . . . . the **Lower** Bound
LU/LD . . . . **l**imit **u**p, **l**imit **d**own
MLE . . . . . **M**aximum **L**og-Likelihood **E**stimation
MSE . . . . . **M**ean **S**quare **E**rror
pdf . . . . . . **p**robability **d**ensity **f**unction
POF . . . . . the **P**roportion **o**f **F**ailures
RGP . . . . . **R**eturn-**g**enerating **P**rocess
SEC . . . . . **S**ecurities and **E**xchange **C**ommission
SSE . . . . . . **S**hanghai **S**tock **E**xchange
TSEC . . . . **T**aiwan **S**tock **E**xchange **C**orporation
Upper . . . . the **Upper** Bound

Distributions

Distribution	Description
CCN	**c**lustered **c**ensored **n**ormal
CN	**c**ensored **n**ormal
CCST	**c**lustered **c**ensored **S**tudent-**t**
$CCST_p$	**c**lustered **c**ensored **S**tudent-**t** with a **p**olynomial form of clusters
$N(\mu, \sigma^2)$	a normal distribution with mean, μ, and standard deviation, σ
GARCH	**G**eneralized **A**uto**R**egressive **C**onditional **H**eteroskedasticity
	abv. as **G** in Table H.0.3
GARCHCN	**GARCH** with **C**ensored **N**ormal innovations
	abv. as **GCN** in Table H.0.3
GARCHCCN	**GARCH** with **CCN** innovations
	abv. as **GCCN** in Table H.0.3
GARCHTN	**GARCH** with **T**runcated **N**ormal innovations
	abv. as **GTN** in Table H.0.3
GARCHST	**GARCH** with **S**tudent-**t**
GARCHCCST	**GARCH** with **c**lustered **c**ensored **S**tudent-**t**
$GARCHCCST_p$	**GARCH** with **c**lustered **c**ensored **S**tudent-**t** with
	a **p**olynomial form of clusters
TN	**t**runcated **n**ormal

Symbols

Symbol	Description
a_1	where the left clusters stops at from *Lower*
b_1	where the right clusters starts from until the value reaches *Upper*
$f(x, \mu, \sigma)$	*pdf* of x and $x \backsim N(\mu, \sigma^2)$
$F(x, \mu, \sigma)$	*cdf* of x and $x \backsim N(\mu, \sigma^2)$
l_1	the left clustering rate of a CCN, $GARCHCCN$, $CCST$, $GARCHCCST$, and $GARCHCCST_p$
m_1	the left clustering coefficient of a CCN, $GARCHCCN$, $CCST$, and $GARCHCCST$
m_2	the right clustering coefficient of a CCN, $GARCHCCN$, $CCST$, and $GARCHCCST$
r_1	the right clustering rate of a CCN, $GARCHCCN$, $CCST$, $GARCHCCST$, $CCST_p$, and $GARCHCCST_p$
pm	the total probability between a_1 and b_1
κ	the constant term in conditional variance process of $GARCH(1,1)$ or $GARCHCN$, $GARCHTN$, $GARCHCCN$, $GARCHCCST$, and $GARCHCCST_p$
α	the coefficient of h_{t-1} in conditional variance process of $GARCH(1,1)$ or $GARCHCN$, $GARCHTN$, $GARCHCCN$, $GARCHCCST$, and $GARCHCCST_p$
β	the coefficient of ${u_{t-1}}^2$ in conditional variance process of $GARCH(1,1)$ or $GARCHCN$, $GARCHTN$, $GARCHCCN$, $GARCHCCST$, and $GARCHCCST_p$
μ	mean
σ	the underlying or the estimated standard deviation
σ^*	the population standard deviation
ρ_1	the left clustering degree coefficient of a $CCST_p/GARCHCCST_p$
ρ_2	the right clustering degree of a $CCST_p/GARCHCCST_p$

Chapter 1

Truncated Normal, Censored Normal, and Clustered Censored Normal

1.1 Literature Review

Various trading limits have been in place worldwide for decades. The main types of trading limits are price limits, circuit breakers, trading halts, and position limits. Price limits confine the trading price of the coming day to a certain range according to the present day's closing price. Circuit breakers prohibit simultaneous trading of an asset and its related futures contracts or options. Trading halts stop all trading activities so as to ease extremely large fluctuations of stock prices or dramatically high trading volumes. Position limits restrict the number of contracts a trader can have at one time. Among these, price limits are most frequently used. For example, the price limits in the Taiwan Stock Exchange Center (TSEC) Weighted Index, the Shanghai Stock Exchange (SSE) Composite Index, the Korea Composite Stock Price Index (KOSPI), and the Cotation Assistée en Continu (CAC)[1] 40 are set as a percentage based on previous day's closing price. The daily percentage limit in TSEC is 7%, in both the SSE Composite Index and CAC 40 is 10%, and in the KOSPI Index is 15%. Price limits are combined with other trading limits. When the price limits are hit, a trading halt is issued for a half hour or more to cool down a market. The Egyptian Stock Exchange has both price limits and a subsequent circuit breaker window. Farag and Cressy (2012) found that the information-spreading pattern follows immediate dissemination hypothesis under simple price limit systems and acts more like sequential dissemination, or market inefficiency when circuit breakers are also implemented.

[1]The CAC 40 is a benchmark French composite index and it takes its name from the Paris Bourse's early automation system Cotation Assistée en Continu.

The history of trading limits in financial markets can be traced from the Black Monday, October 19, 1987, when stock markets world wide shed a huge amount of value in a short period of time. The Brady Commission and the Working Group on Financial Markets recommended remedies to ease extreme fluctuations. From then, price limits have been used in stock markets in Egypt, Japan, Taiwan, France, Korea, China and many other countries. They exist in American futures and options of agricultural commodities, e.g., corn, wheat, oat, and orange juice (Roll (1984)); precious metals, e.g., silver, copper, and gold; and petroleum products, e.g., gas and crude oil; and also in US treasury bill rates (Wei (2002)), government bonds, interest rates in UK [2], and foreign exchange rates in some countries, e.g., Japanese Yen to U.S. dollars (Goldman and Tsurumi (2005)). Debates about their effectiveness and efficiency continued over the past 20 years. Price limit advocates (e.g., Edwards and Neftci (1988, 1991), Arak and Cook (1997), Dark (2011)) suggested that price limits lower volatility, protect stock hedgers, and discourage speculation. In contrast, price limit critics, Telser (1981), Fama (1989), Lehmann and Modest (1989), Ma et al. (1989), Miller (1989), Chen (1998), Huang et al. (2001), Lauterbach and Uri (1993), among others argued that the limits cause volatility spillover, delay price discovery, and interfere with trading.

Furthermore, Brennan (1986) showed that price limits improve the efficiency of futures contract trading if traders are risk neutral and have limited information. Kodres (1994) stated that if prices become too volatile, a short delay of trading can result in a large price change. Then the judiciously chosen price limits were Pareto superior to unconstrained prices. Chou and Lin (2011) suggested that even in a market where traders had abundant information, price limits were useful when traders were risk averse. Price limits deter manipulation (Kim and Park (2010)). In Pakistan, the annual returns of stock brokers' personal equity investments were 50-90 percentage points more than those earned by outsider traders (Khwajia and Mian (2005)). Therefore, price limits are more desirable in markets with higher monitoring costs, greater corruption rates, and lower efficiency in regulatory and technological performance (Deb et al. (2013)).

Another field of price limit literature is on volatility forecasting and model selection. Truncated or censored distributions are employed to restrict variables in a domain. Leading works of truncated normal (TN) and censored normal (CN) include Hald (1949), Cohen (1950, 1954), Gupta (1952), Epstein and Sobel (1953), Amemiya (1973), Nelson (1981), and Schneider (1984). These two models may not have satisfactory empirical performance because the effects of price limits are diverse on both variance and kurtosis. Ma, Rao, and Sears (1989) revealed that price limits provide a cooling off period for futures markets. Kavussanos and Manalis (1999) found that price limits do not affect volatility, but only

[2] For example, as of April 1st, 2014, the payday loans in UK have an initial cost cap of 0.8% per day, fixed default fees capped at £15, and total cap of 100%. Furthermore, Canada, some U.S. states, Netherlands, Poland, Ireland, Japan, Belgium, some Australian states, Slovakia, France, Belgium and many other countries, have interest rate ceilings on consumer credit.

slow down the convergence to the equilibrium price. Kim and Rhee (1997) inferred that although volatility decreases after prices hit the limits, the volatility right afterwards is still higher than that after hitting the 90% or 80% range of limits[3]. Thus, the authors claimed that price limits increase volatility. Kim (2001) observed that wider bounds might not necessarily increase volatility. For kurtosis, Yang and Brorsen (1995) explained thin-tailness in the pork bellies futures return series with price limits while most of stock return series are leptokurtic. In brief, price limits may increase, decrease, or have no effect on volatility and kurtosis.

If CN and TN were appropriate for modelling financial returns with price limits (two sided), variance and kurtosis should have increased as bounds become wider and vice versa. Moreover, clusters are caused by the prohibition of trading outside bounds, behavioural changes due to bounds, the discount rate, and the minimum price difference rule between ticks. In particular, the fluctuation unit (tick) rule makes trading at bounds less likely.

"Operating Rules of the Taiwan Stock Exchange Corporation" stated in Article 62, the fluctuation unit (tick) of the prices of trading orders shall be determined as follows:

"Where the market price of a stock is less than 10 dollars per share, the tick shall be 1 cent, or 5 cents if the price is from 10 dollars to less than 50 dollars, or 10 cents if the price is from 50 dollars to less than 100 dollars, or 50 cents if the price is from 100 dollars to less than 500 dollars, or 1 dollar if the price is from 500 dollars to less than 1000 dollars, or 5 dollars if the price is 1,000 dollars or more. The tick for government bonds and corporate bonds shall be five cents. The tick for convertible bonds shall be 5 cents if the price is less than 150 dollars, or 1 dollar if the price is from 150 dollars to less than 1,000 dollars, or 5 dollars if the price is 1,000 dollars or more."

During a period of exceptionally optimistic or pessimistic expectations of future stock prices, traders relentlessly trade at prices around bounds and so push the prices closer to bounds. This phenomenon, referred as the magnet effect, was investigated in Edwards and Neftci (1988), Lee et al. (1994), Subrahmanyam (1994), Kim and Limpaphayom (2000), Abad and Pascual (2007), Tooma (2011), Cho et al. (2003), and Kim et al. (2013). Hence, to include this so called magnet effect, a class of clustered censored (e.g., clustered censored normal, abbreviated as CCN, as the introductory model) distributions are proposed. The rest of this chapter is organized as follows, Section 1.2 depicts TN, CN, and CCN models, particularly different clusters about bounds; Section 1.3 explores how misspecification of underlying models affects the model estimations and how variance/kurtosis changes with respect to bounds and underlying parameters under Gaussian distribution; Section 1.4

[3] If the upper bound of a stock is $Upper$ and the lower bound is $Lower$, the 90% ranges are $[0.9 * Upper, Upper)$ and $(Lower, 0.9 * Lower]$, and the 80% ranges are $[0.8 * Upper, 0.9 * Upper)$ and $(0.9 * Lower, 0.8 * Lower]$.

compares the fitted TN, CN, and CCN models of 5 Taiwanese, 5 Chinese, 5 Korean, and 5 French stocks by the MLE algorithm; and Section 1.5 concludes and provides suggestions for future research.

1.2 Truncated, Censored, and Clustered Censored normal

Let the lower bound be $Lower$, the upper bound be $Upper$, the underlying mean be μ, and the standard deviation be σ. *pdf* stands for the probability density function and *cdf* stands for the cumulative density function, henceforth. $f(x;\mu,\sigma)$ is the *pdf* of the normal distribution with the mean, μ, and the standard deviation, σ. $F(x;\mu,\sigma)$ is the *cdf*.

Therefore,

$$f(x;\mu,\sigma) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right)$$

1.2.1 Truncated Normal

Let x be a variable with a TN distribution. Let the underlying mean be μ and the underlying standard deviation be σ over the domain $[Lower, Upper]$. The distribution is given by

$$x \sim TN((\mu;\sigma^2), Lower, Upper)$$

pdf_{tn} and cdf_{tn} are the *pdf* and *cdf*. $mean_{tn}$, var_{tn}, $skewness_{tn}$, and $kurtosis_{tn}$ stand for the mean, variance, skewness, and kurtosis. These values are derived in equations A.0.1, A.0.2, A.0.3, and A.0.4 by using $normint_i$'s for $i \in \{1,2,3,4\}$ in Appendix A.

$$pdf_{tn}(x) = \begin{cases} \frac{f(x;\mu,\sigma)}{F(Upper;\mu,\sigma)-F(Lower;\mu,\sigma)} & \text{if} Lower \leq x \leq Upper \\ 0 & \text{else} \end{cases}$$

$$cdf_{tn}(x) = \begin{cases} 0 & \text{if} x < Lower \\ \frac{F(x;\mu,\sigma)-F(Lower;\mu,\sigma)}{F(Upper;\mu,\sigma)-F(Lower;\mu,\sigma)} & \text{if} Lower \leq x \leq Upper \\ 1 & \text{if} x > Upper \end{cases}$$

1.2.2 Censored Normal

Let x be a variable with a CN distribution.

$$x \sim CN((\mu;\sigma^2), Lower, Upper)$$

$mean_{cn}$, var_{cn}, $skewness_{cn}$, and $kurtosis_{cn}$ in equations A.0.7, A.0.8, A.0.9, and A.0.10 are the mean, variance, skewness, and kurtosis derived by using $cnint_i$'s in equations A.0.5 and A.0.6. $i \in \{1, 2, 3, 4\}$

$$pdf_{cn}(x) = \begin{cases} f(x;\mu,\sigma) & \text{if} Lower < x < Upper \\ F(Lower;\mu,\sigma) & \text{if} x = Lower \\ 1 - F(Upper;\mu,\sigma) & \text{if} x = Upper \\ 0 & \text{else} \end{cases}$$

$$cdf_{cn}(x) = \begin{cases} 0 & \text{if} x < Lower \\ F(x;\mu,\sigma) & \text{if} Lower \leq x < Upper \\ 1 & \text{if} x \geq Upper \end{cases}$$

The main difference between TN and CN can be illustrated by the following example. A class of students have an exam that has a grade$\in [0, 17]$ and only people who have a grade greater or equal to 10 pass the exam. The marks of the whole class are a truncated series with the lower bound of 0 and the upper bound of 17. If only the grades of those people who pass the exam and the failing rate are known, this data is censored with the lower bound of 10 and the upper bound of 17. The difference between the shapes of a TN and a CN with the same underlying parameters and bounds is that a CN has the extra clusters right at bounds. [4]

1.2.3 Clustered Censored Normal

Figure 1.2 is the histogram of the stock returns of a Taiwanese stock, Quanta Computer from January 4, 2000 to June 24, 2014. The total number of data is 3554. Figure 1.3 is the histogram of the stock returns of a Taiwanese stock, Nanya Technology from August 8, 2000 to June 24, 2014. The total number of data is 3393. The number of bins used in both figures are 40. The daily limit of a Taiwanese stock is 7%. So the lower and upper bounds shown in these two figures lie almost symmetrically on the two sides of 0 as the values of -7.2571 and 6.7659. Figure 1.3 has more obvious clusters about the bounds than figure 1.2. Therefore, it might be useful to have a distribution with parameters that define different ranges and shapes of clusters.

Figure 1.1 presents the shape of a *pdf* curve of a typical CCN distribution. The *pdf* of this CCN consists of three main segments: The *pdf* in $x \in [-4, -2]$ is referred as the left clusters; the *pdf* in $x \in [-2, 2]$ is similar to normal distribution; the *pdf* in $x \in [2, 4]$ is the right clusters. The *pdf* for any value outside of the domain $[-4, 4]$ is 0. This distribution

[4] Stock return series touch the bounds more frequently than an index price series, so stock returns tend to behave like a censored distribution and indices are more likely to be truncated distributions.

Figure 1.1: *pdf* of a typical *CCN*

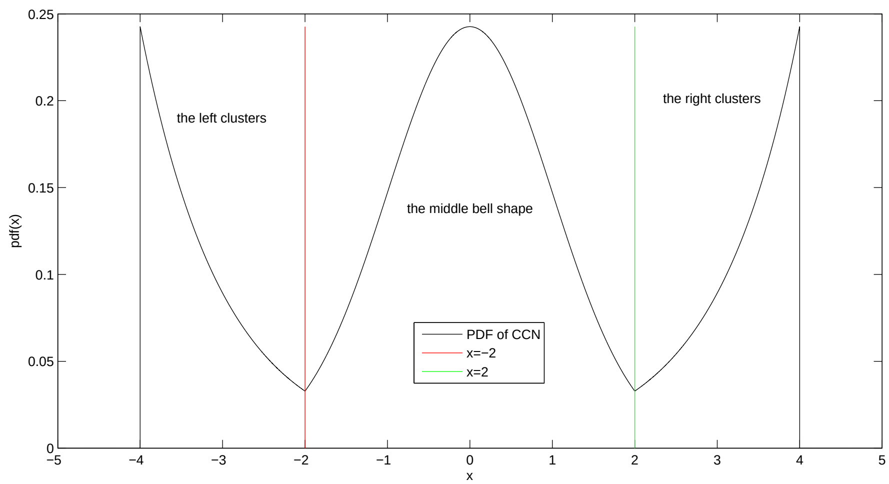


Figure 1.2: Histogram of Quanta Computer

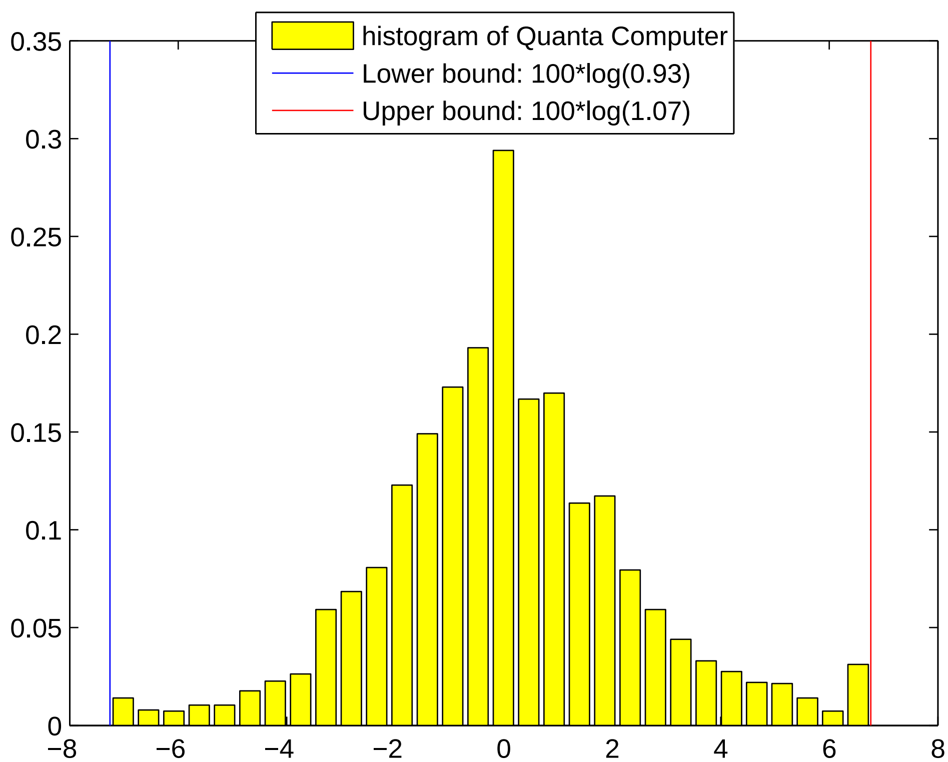
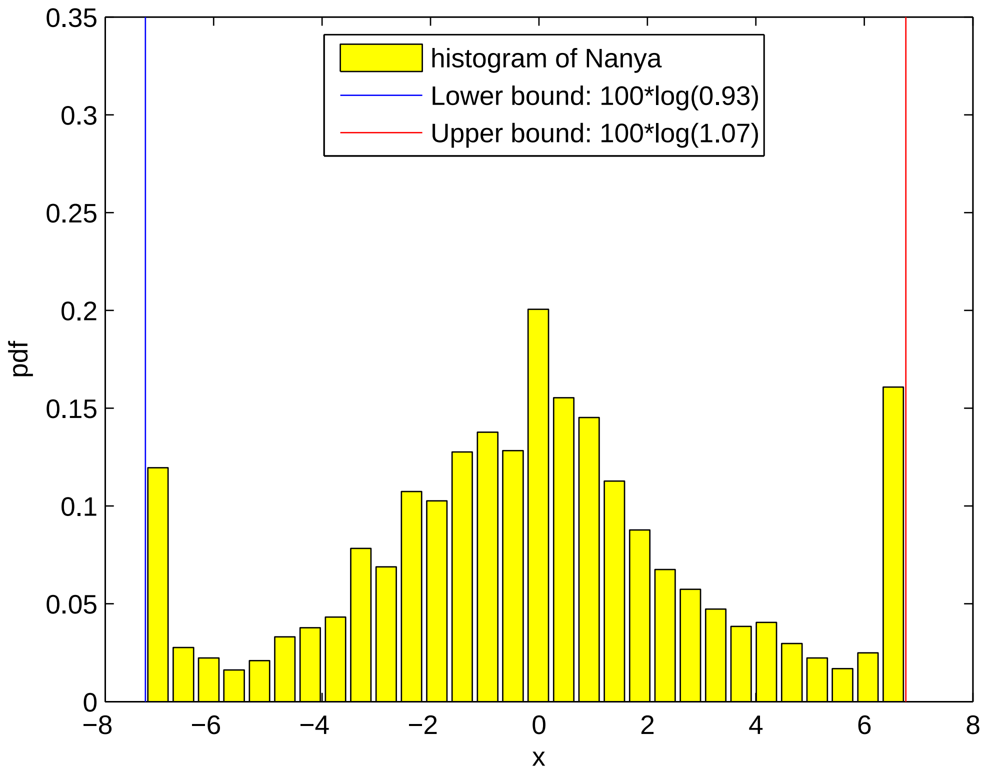


Figure 1.3: Histogram of Nanya



is a CCN, in which the underlying mean is 0, the underlying standard deviation is 1, the clustering rate[5] around *Lower* is 0.5, the clustering rate around *Upper* is 0.5, the left clustering coefficient is -1, the right clustering coefficient[6] is 1, and the domain is $[-4, 4]$.

Having seen an example of CCN, we formally introduce the distribution in details. The underlying mean is μ. The underlying standard deviation is σ. The left clustering rate is l_1 and the right clustering rate is r_1. The left clustering coefficient is m_1 and the right clustering coefficient is m_2. The lower bound is *Lower* and the upper bound is *Upper*. Let $Lower < \mu$ and $Upper > \mu$. The distribution is given by

$$x \sim CCN((\mu; \sigma^2; l_1; r_1; m_1; m_2), Lower, Upper)$$

Let $a_1 = \mu + (Lower - \mu) * l_1$ and $b_1 = \mu + (Upper - \mu) * r_1$.

The clustering rates, $l_1, r_1 \in [-1, 1]$, and the values are well defined as long as $Lower \leq a_1 \leq b_1 \leq Upper$. The values of the clustering rates are not restricted inside of $[0, 1]$ because we can have a CCN that has the underlying distribution to be standard normal, l_1 to be -0.03, and r_1 to be 0.7. Thus, a_1 is 0.12 and b_1 is 2.8. $a_1 \leq b_1$ is satisfied in this case.

Let $A = f(a_1; \mu, \sigma)$ and $B = f(b_1; \mu, \sigma)$. If $Lower \leq x \leq a_1$, the *pdf* is proportional to the curve expressed as $A * \exp(m_1 * (x - a_1))$. If $a_1 \leq x \leq b_1$, $pdf_{ccn}(x)$ is proportional to the *pdf* of a normal distribution that is $f(x; \mu, \sigma)$. If $b_1 \leq x \leq Upper$, $pdf_{ccn}(x)$ is proportional to the curve shown as $B * \exp(m_2 * (x - b_1))$. m_1 and m_2 reflect how steep the clusters are around the lower and upper bounds. A value Ω is included in the *pdf* in order to satisfy these two conditions:

1. $cdf_{ccn}(Lower, (\mu; \sigma^2; l_1; r_1; m_1; m_2), Lower, Upper) = 0$ and $cdf_{ccn}(Upper, (\mu; \sigma^2; l_1; r_1; m_1; m_2), Lower, Upper) = 1$

2. $cdf_{ccn}(x, (\mu; \sigma^2; l_1; r_1; m_1; m_2), Lower, Upper)$ is a non-decreasing function.

To define the *pdf*, *cdf*, and the first four moments of a CCN, $L_i(y, (\mu; \sigma^2; l_1; r_1; m_1; m_2), Lower, Upper)$, L_i, $M_i(y, (\mu; \sigma^2; \mu; \sigma^2; l_1; r_1; m_1; m_2), Lower, Upper)$, M_i, $R_i(y, (\mu; \sigma^2; \mu; \sigma^2; l_1; r_1; m_1; m_2), Lower, Upper)$, and R_i in equations B.0.2, B.0.4, B.0.7, B.0.8, B.0.9, and B.0.12 are used. If $m_1 \neq 0$, let $L_0 = \int_{Lower}^{a_1} A * \exp(m_1 * (x - a_1))dx = A(1 - exp(Lower - a_1))/m_1$; otherwise, $L_0 = A * (a_1 - Lower)$. $M_0 = \int_{a_1}^{b_1} f(x; \mu, \sigma)dx$. If $m_2 \neq 0$, $R_0 = \int_{b_1}^{Upper} B * \exp(m_2 * (x - b_1))dx = B(exp(Upper - b_1) - 1)/m_2$; otherwise, $R_0 = B * (Upper - b_1)$.

[5] If the left clustering rate is l_1, the left clusters are in the domain $[Lower, l_1 * (Lower - \mu) + \mu]$. Similarly, the right clustering rate r_1 defines the right clusters to be in $[r_1 * (Upper - \mu) + \mu, Upper]$.

[6] The left and right clustering coefficients decide the shapes of the clusters.

$$\Omega = L_0 + F(b_1;\mu,\sigma) - F(a_1;\mu,\sigma) + R_0 \tag{1.2.1}$$

The *pdf* and *cdf*[7] of x are computed by using $L_0(x,(\mu;\sigma^2;l_1;r_1;m_1;m_2),Lower,Upper)$, $M_0(x,(\mu;\sigma^2;l_1;r_1;m_1;m_2),Lower,Upper)$, and $R_0(x,(\mu;\sigma^2;l_1;\ r_1;m_1;m_2),Lower,Upper)$ in equations B.0.10, B.0.7, B.0.5, B.0.13, and B.0.9,

$$pdf_{ccn}(x,(\mu;\sigma^2;l_1;r_1;m_1;m_2),Lower,Upper) = \begin{cases} \frac{f(x;\mu,\sigma)}{\Omega} & \text{if} a_1 \le x \le b_1 \\ \frac{\exp(m_1(x-a_1))A}{\Omega} & \text{if} Lower \le x \le a_1 \\ \frac{\exp(m_2(x-b_1))B}{\Omega} & \text{if} b_1 \le x \le Upper \\ 0 & \text{else} \end{cases}$$

$$cdf_{ccn}(x) = \left\{ \begin{array}{ll} 0 & \text{if} x < Lower \\ \frac{L_0(x,(\mu;\sigma^2;l_1;r_1;m_1;m_2),Lower,Upper)}{\Omega} & \text{if} Lower \le x \le a_1 \\ \frac{L_0+M_0(x,(\mu;\sigma^2;l_1;r_1;m_1;m_2),Lower,Upper)}{\Omega} & \text{if} a_1 \le x \le b_1 \\ \frac{L_0+M_0+R_0(x,(\mu;\sigma^2;l_1;r_1;m_1;m_2),Lower,Upper)}{\Omega} & \text{if} b_1 \le x \le Upper \\ 1 & \text{if} x > Upper \end{array} \right\}$$

Let pm be the probability between a_1 and b_1[8]. Equations B.0.3, B.0.8, B.0.6, B.0.14, and B.0.12 compute L_i, M_i, R_i for $i = 0,1,2,3,4$ [9]. Consequently, the mean, variance, skewness, and kurtosis of x are expressed as $mean_{ccn}$, var_{ccn}, $skewness_{ccn}$, and $kurtosis_{ccn}$.

$$\begin{aligned} mean_{ccn}((\mu;\sigma^2;l_1;r_1;m_1;m_2),Lower,Upper) &= E(x) \\ &= (L_1 + M_1 + R_1)/\Omega \end{aligned} \tag{1.2.2}$$

$$E(x^2) = (L_2 + M_2 + R_2)/\Omega \tag{1.2.3}$$

$$var_{ccn}((\mu;\sigma^2;l_1;r_1;m_1;m_2),Lower,Upper) = E(x^2) - (E(x))^2 \tag{1.2.4}$$

The value of $var_{ccn}((\mu;\sigma^2;l_1;r_1;m_1;m_2),Lower,Upper)$ can be obtained by using equations 1.2.2 and 1.2.3.

$$E(x^3) = (L_3 + M_3 + R_3)/\Omega \tag{1.2.5}$$

[7] To save space, $cdf_{ccn}(x,(\mu;\sigma^2;l_1;r_1;m_1;m_2),Lower,Upper)$ is denoted as $cdf_{ccn}(x)$ in the definition below.

[8] We use pm to compare the proportion in the clusters among different stocks. We don't have a critical value of pm, by which we claim the pm value is large or small.

[9] The definitions of these values are explained in Appendix B.

$\sigma^* = \sqrt{var_{ccn}((\mu;\sigma^2;l_1;r_1;m_1;m_2), Lower, Upper)}$ is the population standard deviation.

$$\begin{aligned} skewness_{ccn}((\mu;\sigma^2;l_1;r_1;m_1;m_2), Lower, Upper) &= skewness(x) \\ &= E\left(\frac{(x-mean(x))^3}{((\sigma^*)^2)^{\frac{3}{2}}}\right) \\ &= \frac{E(x^3) + 2*(E(x))^3 + 3*E(x^2)*E(x)}{(\sigma^*)^3} \end{aligned} \tag{1.2.6}$$

The value of $skewness_{ccn}((\mu;\sigma^2;l_1;r_1;m_1;m_2), Lower, Upper)$ can be calculated by using equations 1.2.2, 1.2.3, and 1.2.5.

$$E(x^4) = (L_4 + M_4 + R_4)/\Omega \tag{1.2.7}$$

$$\begin{aligned} kurtosis(x) &= kurtosis_{ccn}((\mu;\sigma^2;l_1;r_1;m_1;m_2), Lower, Upper) \\ &= E\left(\frac{(x-mean(x))^4}{((\sigma^*)^2)^2}\right) \\ &= \frac{E(x^4) + 6(E(x))^2E(x^2) - 4E(x)E(x^3) - 3(E(x))^4}{(\sigma^*)^4} \end{aligned} \tag{1.2.8}$$

The value of $kurtosis_{ccn}((\mu;\sigma^2;l_1;r_1;m_1;m_2), Lower, Upper)$ can be found by using equations 1.2.2, 1.2.3, 1.2.5, and 1.2.7.

The next section presents Monte Carlo simulations on estimations under TN, CN, and CCN. From the outcomes of the Monte Carlo simulations, it is shown that even when we do not know the true distribution of a data series, clustered censored distribution can contain special cases, e.g., normal, truncated and censored distributions, and the Laplace distribution. In particular, both the clusters about bounds and the diverse changes of both variance and kurtosis with respect to the changes of bounds (depicted as the '$variance-b$' and '$kurtosis-b$' curves in figures D.1 and D.2) are satisfied by using CCN. Furthermore, we will show in the empirical evidence section that it is very likely that financial returns with limits are clustered censored. Therefore, it is important to see under Gaussian, the possible outcomes (in particular, the biases of parameter estimates) of our decision and assessment to use unlimited, truncated, censored, or clustered censored model.

1.3 Monte Carlo Simulations

In this section, several experiments of Monte Carlo simulations are conducted to illustrate the statistical properties of TN, CN, and CCN. In particular, we investigate how the bounds affect the parameter estimation if the true model is either TN or CN and how parameters estimations react on changing bounds and underlying parameters if the true model is CCN. The experiments have data size of either 500 or 5000, and the repetition number is 1000. Table C.0.1 lists the experiments performed, for example, experiment 1 uses TN as the true model and the bounds are $[-4, 4]$, $[-3.8, 3.8]$, $[-3.6, 3.6]$, $[-3.4, 3.4]$, $[-3.2, 3.2]$, $[-3, 3]$, $[-2.8, 2.8]$, $[-2.6, 2.6]$, $[-2.4, 2.4]$, $[-2.2, 2.2]$, and $[-2, 2]$ (table C.0.2). If the data size is changed from 5000 to 500, the estimates of experiment 2 are presented in table C.0.3. Similarly, the estimates of CN simulations with respect to different bounds are in tables C.0.4 and C.0.5. For CCN, the estimate changes with respect to bounds are in tables C.0.6 and D.0.2. Those with respect to clustering coefficients are in C.0.7 and D.0.3. Changes with respect to clustering rates with data sizes of 5000 and 500 are in tables C.0.8 and D.0.4.

All these above-mentioned simulations have underlying mean, 0. The corresponding estimates in tables C.0.2, C.0.3, C.0.4, and C.0.5 reveal that the means estimated by using either the underlying model or normal are just close to the underlying mean in symmetric simulations. The estimate of the standard deviation by using the true model are closer to its real value, 1, than that from other models. Furthermore, the standard deviation estimated by normal model is the population standard deviation of the simulated data. The population standard deviation of CN simulations is greater or equal to that of TN when given the same underlying mean, standard deviation, and bounds. This fact is consistent with figure D.1 and it will be elaborated later in this chapter.

Moreover, experiment 5 sets the bounds for CCN to be $[-12, 12]$, $[-10, 10]$, $[-6, 6]$, $[-4, 4]$, $[-3, 3]$, and $[-2, 2]$. If only the data size in experiment 5 is changed from 5000 to 500, the outcomes of experiment 8 are obtained. The *pdf*s of each pair of bounds are plotted in figure D.4. As bounds grow, the distribution converges to its underlying normal distribution (figure D.4). Experiment 6 is the same as experiment 5, but with a underlying mean of 0, a underlying σ of 1, both clustering rates of 0.5, and a domain of $[-3, 3]$. The values of m_1 and m_2 are symmetric about y-axis, including -2 and 2, -1 and 1, 0.3 and -0.3, 1 and -1, and 2 and -2. The corresponding *pdf* shapes are in figure D.6. As the left clustering coefficient decrease, and the right one increases, the clusters have steeper shapes and the *pdf* curves are more likely to have 'W' shapes. If only the data size is changed from 5000 to 500, experiment 9 is performed. Experiment 7 is the same as experiment 5, but with an underlying mean of 0, an underlying σ of 1, m_1 and m_2 of -2 and 2, and a domain of $[-3, 3]$. The values of clustering rates are equal, including 0.2, 0.5, 0.6 and 0.8. If only the data size is changed from 5000 to 500, experiment 10 is performed.

Based on these Monte Carlo simulations, tables C.0.6, D.0.2, and figure D.4 show that our simulations are in the range where variance is above the underlying variance (figure D.1). Therefore, the population standard deviation, σ^* increases and then converges to the underlying σ. In fact, normal, CN, TN, the Laplace distribution[10] are special cases of CCN. If bounds converge to $(-\infty, \infty)$, l_1 and r_1 both greater than 0, a CCN distribution converges to a normal distribution. A CCN with l_1 and r_1 both arbitrarily close to 1, the *pdf* at the lower bound equal to $F(Lower; \mu, \sigma)$, and the *pdf* at the upper bound equal to $1-F(Upper; \mu, \sigma)$, resembles a CN. A CCN with l_1 and r_1 both equal to 1 is a TN. When l_1 and r_1 are 0 and bounds are $(-\infty, \infty)$, CCN converges to the Laplace distribution if $m_1 = \frac{1}{\varrho} > 0$ and $m_2 = -m_1$.

To justify these superior-subordinate relationship, we plot the fitted normal, TN, CN, and CCN in the third row in table C.0.2 given the true model, a TN with mean of 0, σ of 1, and bounds of $[-2, 2]$, in figure C.1. In figure C.2, the underlying model is CN with mean of 0, σ of 1, and bounds of $[-2, 2]$. The fitted models are from the third row in table C.0.4. In figure C.3, the fitted models in the last row in C.0.6 are plotted. The underlying model is CCN with mean of 0, σ of 1, clustering rates of 0.5, clustering coefficients of -2 and 2, and bounds of $[-2, 2]$. These three figures illustrate that CCN can be trusted to find the underlying distribution even when the true model is either CN or TN, but not the other way around. Similarly, figures D.3a, D.3c, D.3b, and D.3d show that CCN can be transformed to normal, TN, CN, and the Laplace with certain restrictions upon parameters and bounds.

Generally speaking, σ^* converges to its underlying value as *pm* becomes bigger in CCN simulations. As m_1 increases and/or m_2 decreases, *pm* rises (tables C.0.7 and D.0.3). As l_1 and/or r_1 increase(s), *pm* increases (tables C.0.8 and D.0.4). As bounds become wider, *pm* is bigger (tables C.0.6 and D.0.2).

For asymmetric simulations, table D.0.1 shows that as bounds become wider, the biases of mean and standard deviation estimations by normal model decrease in CN, TN, and CCN simulations. In addition, as the clusters have a wider range, e.g., the left and/or right clustering rates decrease, or steeper clustering shapes about the bounds, e.g., the left and/or right clustering coefficients have greater absolute values (and the left clustering coefficient is smaller than 0 and the right clustering coefficient is greater than 0), the biases of both mean and standard deviation estimated by normal model increase. Yet the biases of mean estimates are not influenced by the changes of bounds in symmetric simulations.

Furthermore, figures D.1 and D.2 display how the variance and kurtosis change with respect to bounds, denoted as $[-b, b]$ and $b \in [0, 10]$ for TN, CN, and CCN models. These figures show that CCN satisfies the above-mentioned diverse changes of variance and kurtosis

[10] The pdf of a Laplace distribution with mean of μ and a scale parameter of $\varrho > 0$, is shown as the following function,

$$pdf_{Laplace}(x, (\mu; \varrho)) = \frac{1}{2\varrho} \exp(-\frac{|x-\mu|}{\varrho})$$

with respect to bounds, e.g., in Kim (2001). The variance and kurtosis of CN are higher or equal to those of TN if the two distributions have the same underlying parameters and bounds. Similarly, the variance and kurtosis of CCN is greater or equal than that of either CN or TN if all these three distributions have the same underlying parameters and bounds. Although this may be true, if b is smaller than the underlying standard deviation, the kurtosis of a CCN might be smaller than those of CN and TN. The variance of a CCN can either be greater or smaller or equal to its underlying variance, but the variances of CN or TN can only be smaller or equal to their underlying variances.

The '$variance - b$'[11] curve for a CCN pivots up and to the right if l_1 and/or r_1 decrease(s), as shown from the comparisons between the curves defined as '$variance\ of\ CCN\ if\ pa = (0; 1; 0.6; 0.6; -1; 1)$' and '$variance\ of\ CCN\ if\ pa = (0; 1; 0.7; 0.7; -1; 1)$'. The '$variance - b$' curve pivots up and to the right and has a higher peak if m_1 is smaller and/or m_2 is larger, which can be seen from the curves defined as '$variance\ of\ CCN\ if\ pa = (0; 1; 0.6; 0.6; -1; 1)$', '$variance\ of\ CCN\ if\ pa = (0; 1; 0.6; 0.6; -2; 2)$', and '$variance\ of\ CCN\ if\ pa = (0; 1; 0.6; 0.6; 1; -1)$'. The '$kurtosis - b$' [12] curves have similar changing patterns with respect to the underlying parameters and bounds as the '$variance - b$' curves. The flexible values of variances, kurtoses, the ranges of clusters, and the shapes of clusters are practical for different doubly limited stock returns (figures 1.2 and 1.3).

1.4 Empirical Evidence

Let p_t be the adjusted closing price of the stock at the time period t.

$$u_t = 100log\left(\frac{p_t}{p_{t-1}}\right) \tag{1.4.1}$$

The starting and ending dates of 5 Taiwanese, 5 Chinese, 5 Korean, and 5 French stocks are presented in table E.0.1. The minimum and maximum of each stock are each $100*log(1-r)$ and $100*log(1+r)$, and r is the daily percentage limit. The fitted normal, TN, CN, and CCN models by the MLE algorithm for each stock return series are summarized in table E.0.3.

Let k be the number of parameters, for example, $k = 6$ for CCN and $k = 2$ for all other models; T is the number of values in u. $LOGL$ is the log-likelihood value.

$$AIC = 2k - 2LOGL$$

[11]In this figure, variance values are plotted with respect to the value of b, which defines the bounds as $[-b, b]$.

[12]In this figure, kurtosis values are plotted with respect to the value of b, which defines the bounds as $[-b, b]$.

$$BIC = k * log(T) - 2LOGL$$

Table E.0.3 reveal that CCN has the smallest AIC and BIC in every stock, and the evidence against higher BIC is very strong for every stock according to table E.0.2 (Kass and Raftery (1995))[13]. The AIC and BIC values of normal, TN, and CN are very close in each stock. The pm's of the fitted CCN models are different and they are in a range of $[0.4911, 0.9729]$. The pm's of Iljin Electric Co Ltd is the highest in all the 20 stocks in this chapter. Most of the pm's are above 0.8 except Nan Kang (0.7353), China MinSheng Bank (0.5463), Hansol Artone Paper Co. Ltd (0.7632), Phoenix (0.6785), and Carrefour (0.4911).

Figures E.1a, E.1b, E.1c, E.1d, E.2a, E.2b, E.2c, E.2d, E.3a, E.3b,E.3c, E.3d, E.4a, E.4b, E.4c, E.4d, E.5a, E.5b, E.5c, and E.5d include the histogram, the fitted normal curve, TN, CN, and CCN all in one figure for the stocks in table E.0.1. The pdf curves for the fitted normal, TN, and CN models are similar for each stock, so TN or CN may not significantly improve data fitting compared to normal model. The fitted CCN has a narrower shape around the peak and thicker ends around the two bounds than other fitted models in each stock. If the clustering rates are closer to 1, the left clustering coefficient is smaller than -1, and the right clustering coefficient is greater than 1, the clusters are obvious and the *pdf* curve of the fitted CCN has a 'W' shape, e.g., Tung Kai Technology in figure E.1b. In contrast, if the clustering rates are closer to 0, the left clustering coefficient is greater than -1, and the right clustering coefficient is smaller than 1, the clusters are not obvious and the *pdf* shapes are similar to those in figures E.5c and E.5d. The nuance of clusters is usually accompanied with smaller l_1 and r_1. In addition, the left and right clusters are not symmetric in each stock, but the levels of asymmetry vary: ShinWoo Co., Ltd and Borneo International Furniture BIF Co Ltd in figures E.3c and E.3d have steeper right clusters but Nan Kang and China Merchants in figures E.2a and E.2c have almost symmetric clusters.

1.4.1 cdf Comparisons

It is important to compare the *cdf* of the empirical data with those of each fitted models to measure the goodness of fit. *cdf* comparisons are related to the values at risk (VaRs) forecast in next chapter. It is shown in figures E.6a, E.6b, E.6c, E.6d, E.7a, E.7b, E.7c, E.7d, E.8a, E.8b, E.8c, E.8d, E.4a, E.9b, E.9c, E.9d, E.10a, E.10b, E.10c, and E.5d, that CCN is better at tracing the *cdf* curve of each data than other models. Even when the clusters at zero are obvious in the *cdf* plots of Taiflex, Tung Kai, Tri Ocean, Jye Tai,

[13] These benchmark values are derived in Kass and Raftery (1995). B_{10} is the likelihood ratio or the Bayes factor, $pr(D/H_1)/pr(D/H_0)$, in which D is the data, H_1 is the hypothesis that favours model 1, H_0 is the hypothesis that favours model 0, and pr stands for the probability. The difference between the two BICs of two different models can be approximated by twice the logarithm of the Bayes factor. To have a very strong evidence against model 0, B_{10} must be greater than 150 and thus $2log(B_{10})$ must be greater than 10. Page 777 in Kass and Raftery (1995) and Jeffreys (1961, app. B) provide more details on how to choose the critical values.

Nan Kang, GD Power, and Inner Mongolia Baotou, the *cdf*s of fitted CCN are the best approximation of the empirical *cdf*s. In particular, in Hansol, AirBus, Essilor, Bouygures, Carrefour, and Renault, the CCN *cdf*s are almost identical to their empirical *cdf*. In addition, we do not find there is a relation between pm values and the impact of clusters on deviating *pdf* and *cdf* of a CCN from those of other three fitted models. Figures E.10c and E.9b show very similar differences in *cdf* curves among four fitted models while the pm values are very different, 0.4911 and 0.9729.

1.4.2 Clusters at zero

There is concern on clusters at zero. The Laplace distribution can have a sharp peak at its median. Therefore, we want to add cluster censored property to the Laplace distribution to see if the distribution can capture the clusters at zero. Let $A = pdf_{Laplace}(a_1, (\mu; \varrho))$ and $B = pdf_{Laplace}(b_1, (\mu; \varrho))$.

$$cdf_{Laplace}(x, (\mu; \varrho)) = \begin{cases} \frac{exp(\frac{x-\mu}{\varrho})}{2} & \text{if} x < \mu \\ 1 - \frac{exp(-\frac{x-\mu}{\varrho})}{2} & \text{if} x \geq \mu \end{cases}$$

In the following equation, the definitions of L_0 and R_0 are exactly the same as those in equation 1.2.1 only except the changes of values A and B,

$$\Omega_{cclaplace} = L_0 + cdf_{Laplace}(b_1, (\mu; \varrho)) - cdf_{Laplace}(a_1, (\mu; \varrho)) + R_0 \tag{1.4.2}$$

A clustered censored *Laplace* distribution, abbreviated as $CCLaplace$, has the following *pdf*,

$$pdf_{cclaplace}(x, (\mu; \varrho; l_1; r_1; m_1; m_2), Lower, Upper) = \begin{cases} \frac{\frac{exp(-\frac{|x-\mu|}{\varrho})}{2\varrho}}{\Omega_{cclaplace}} & \text{if} a_1 \leq x \leq b_1 \\ \frac{\exp(m_1(x-a_1))A}{\Omega_{cclaplace}} & \text{if} Lower \leq x \leq a_1 \\ \frac{\exp(m_2(x-b_1))B}{\Omega_{cclaplace}} & \text{if} b_1 \leq x \leq Upper \\ 0 & \text{else} \end{cases}$$

Figures 1.4 and 1.5 have clusters at zero. There are 500 bins in the histogram of Microsoft Corporation stock returns because this company has much more data, from March 13, 1986 to September 16, 2015. The stagnant stock prices exist in mature companies that are unable to find large growth opportunities. The clusters at zeros as shown in the histogram of stock returns of Microsoft Corporation in figure 1.5 are due to the lack of new technologies and initiatives to dramatically increase investment and productivity, and the payouts of dividends. These reasons can explain the clusters at zeros for other stock

Figure 1.4: Histogram (30 bins) and Fitted Curves: Taiflex

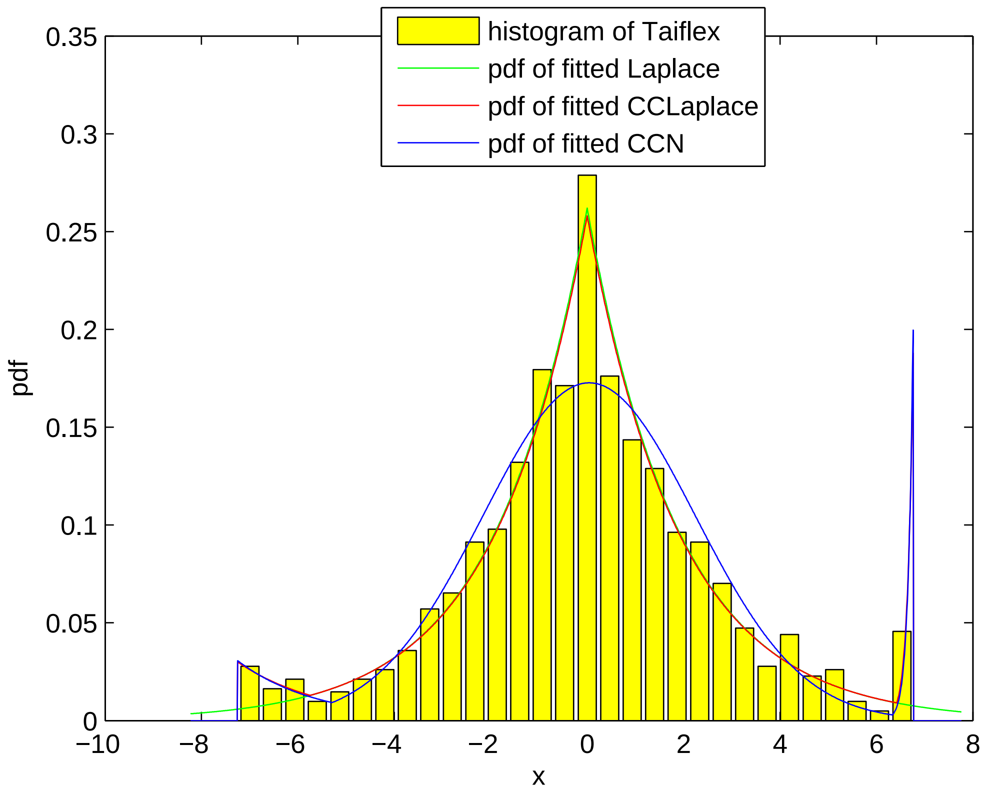


Figure 1.5: Histogram (500 bins) of Microsoft Corporation

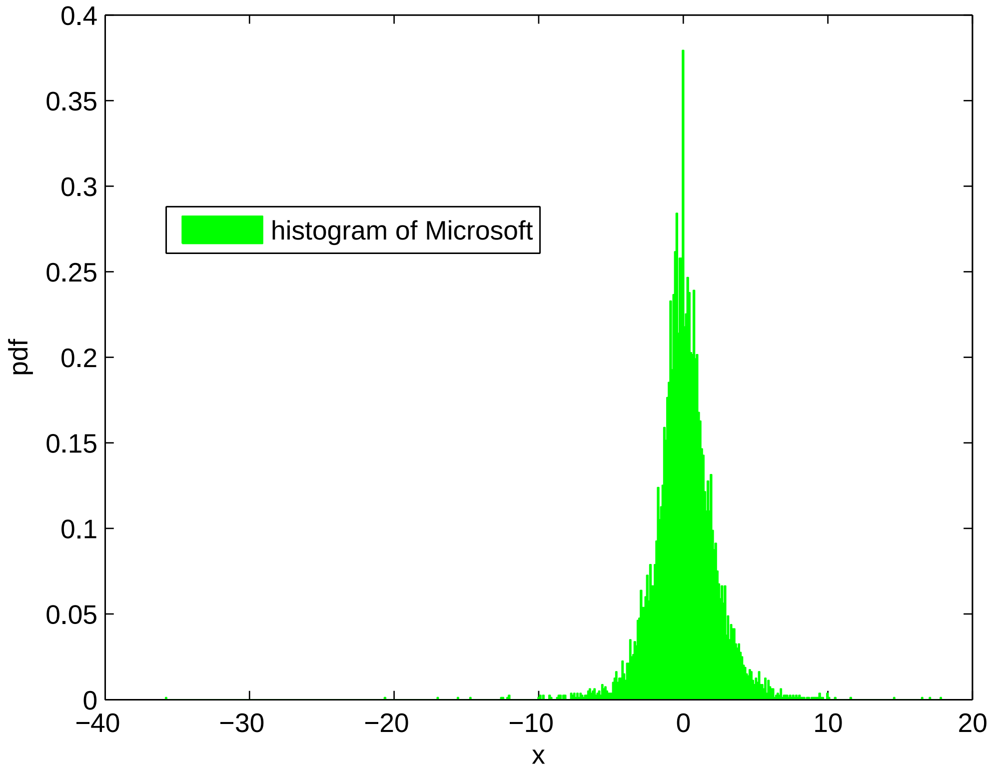


Table 1.4.1: Fitted Laplace and clustered censored Laplace

Model	μ	ϱ	l_1	r_1	m_1	m_2	$-LOGL$	BIC
Taiflex								
Laplace	0.0000	1.9076***					3.1272e+003	6.2688e+003
	(0.0000)	(0.0522)						
bounds are [100*log(0.93),100*log(1.07)]								
CCLaplace	0.0000	1.9184***	0.7919***	0.9492***	-0.5608	8.9508	3.0358e+003	**6.1148e+003**
	(0.0005)	(0.0718)	(0.0262)	(0.0079)	(0.2546)	(1.9730)		
CCN	0.0407	2.2024***	0.7306***	0.9357***	-0.6138**	9.8839***	3.0587e+003	6.1318e+003
	(0.0449)	(0.0499)	(0.0209)	(0.0094)	(0.2137)	(1.9981)		

Notes: $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$

returns. From the comparison between the bounded and unbounded histograms in figures 1.4 and 1.5, we infer that clusters at zero are not caused by bounds. On the contrary, the clusters at bounds are ostensible in figure 1.4 but not 1.5. In figure 1.4, both CCN and $CCLaplace$ are able to capture the clusters at bounds. These two fitted models illustrate almost identical ranges and shapes of clusters while the fitted Laplace and $CCLaplace$ have similar *pdf* shapes in the middle section, the domain inside of the bounds except the clustering ranges. In conclusion, the Laplace distribution can help to capture clusters at zero. However, from table 1.4.1, the BIC of fitted Laplace is much greater than those of other two models while the difference between the $BICs$ of fitted $CCLaplace$ and CCN is relatively small. We suggest that it is more important to accommodate clusters at bounds than clusters at zero to improve a model's goodness of fit.

1.5 Conclusions

In this chapter, Monte Carlo simulations are used to show that if the real model is TN, the true standard deviation is under estimated by 12.02%[14] if bounds are ignored (while in fact, bounds are $[-2, 2]$ in C.0.2). Given the same underlying parameters and bounds, if the real model is CN, the underlying standard deviation is under estimated by 4.24% in C.0.4. If the real model is CCN with clustering rates of 0.5, and the left and right clustering coefficients of -2 and 2, the true standard deviation is over estimated by 42.80% in C.0.6 if bounds are overlooked. Likewise, if the true distribution is $CCN((0.1; 1; 0.7; 0.7; -2; 2), -3, 3)$, the μ and standard deviation estimated by normal model have an upward bias of 70.80% and an upward bias of 41.49% respectively in table D.0.1. Subsequently, the all-in-one figures

[14] A bias is the absolute difference between the parameter estimate and the true value in Monte Carlo simulation. When the bias is presented in percentage term, the bias is equal to the absolute difference divided by the true value. If the parameter estimate is greater than the true value, there is an upward bias; otherwise, there is a downward bias.

and the superior-subordinate relationship validate the fact that the resemblances between the histograms of data series and the *pdf* curves of the corresponding fitted CCN models are much closer than those between the histograms of data series and the *pdf* curves of the fitted normal, CN, and TN models.

CCN is a special case of a mixture distribution. It is not possible to have a traditional finite Gaussian mixture distribution that has clusters unless we use a mixture of half normal distributions. We will investigate this type of mixture distributions more in our future work.

Furthermore, volatility clustering has often been discussed in research about financial time series. Different models, e.g., the generalized autoregressive conditional heteroskedasticity ($GARCH$, Bollerslev (1986)) and stochastic volatility models are recommended to characterize this feature. $VaRs$ have been frequently used by both financial institutes and regulatory agencies to access the credit rating and minimum capital required to cover the risk. In section 1.4.1, the comparisons of *cdf* curves among fitted models give a hint that better VaR estimation can be achieved by using a clustered censored time series model rather than its unlimited, censored, or truncated counterparts. Hence, in Chapter 2, we extend clustered censored property into a time varying volatility model in hope of improving both in-sample and out-of-sample VaR forecasts.

Chapter 2

$GARCH(p, q)$ with clustered censored normal innovations

2.1 Literature Review

Financial institutes nowadays provide services for clients worldwide. Research on financial returns with price limits are of interest since bounds exist in Korea, Taiwan, France, China, and many other countries, and numerous types of financial markets, e.g., futures and options of precious metals, petroleum goods, and agricultural products in the U.S., as mentioned above in Chapter 1. Furthermore, the debates about government intervention in market economy heat up after the recent global economic downfall beginning in year 2007. Starting from April 8, 2013, a "limit up, limit down" (LU/LD) under Securities and Exchange Commission (SEC) regulations replaced circuit breaker in which a limit state was imposed if a stock's trading volume increased or decreased by 10% within a rolling five-minute window.

The reference price of the current LU/LD rule is the average of trading prices over the preceding five minute and it is adjusted every 30 seconds if there are 1% change in the price. If trading limit (a percentage limit of 10% based on the reference price) are met, that stock enters into a limit state[1] for 15 seconds. Therefore, it is important to find models that contain special characteristics due to the existence of limits.

Several approaches were used in the research on volatility forecasting of financial returns with price limits. Hodrick and Srivastava (1987) and McCurdy and Morgan (1987, 1989) proposed to either ignore or delete price limits. To ignore the price limits means treating

[1]A limit state ends only if one of the followings happens: a trade offered within the bounds/bands is made, the offers sitting on the bounds/bands are cancelled or modified, and the bounds can be changed so the offers no longer sit on the bounds/bands.

data as if there were no limits. To delete the price limits means that all financial returns hitting the limits are removed. Wei and Chiang (1997) criticized these two proposals by arguing that the estimated standard deviation for Japanese yen futures during 1977-1979 had a downward bias of 5.7% if price limits were ignored and of 14.3% if the limits were deleted. Furthermore, clusters around the limits may also cause complications besides the bounds (Edwards and Neftci (1988), Lee et al. (1994), Subrahmanyam (1994), Kim and Limpaphayom (2000), Abad and Pascual (2007), Tooma (2011), and Kim et al. (2013)). McCurdy and Morgan (1987) suggested changing data from daily to weekly. This suggestion is not appropriate because data size decreases substantially and limits still exist every day. Moreover, weekly limits are seven times of daily limits and weekly data may not be affected by limits as much as daily data.

Since financial data consistently exhibit volatility clustering, time varying conditional variance processes are used. One benchmark model is the $GARCH$ model in Bollerslev (1986). Wei (2002) proposed a censored-$GARCH$ process using the Bayesian method with an application to Treasury bill futures over a period of high volatility and frequent limit moves. Goldman and Tsurumi (2005) depicted a Markov chain sampling approach, a method primarily proposed by Nakatsuma (2000), with a doubly truncated $ARMA-GARCH$ model on the Japanese Yen to U.S. dollar exchange rate over a specific period of stringent constraint. Yang et al. (2009) demonstrated the usefulness of the Bayesian approach with a censored stochastic volatility model, by modelling the returns of two actively traded stocks on the Taiwan Stock Exchange and two U.S. futures contracts on the Chicago Board of Trade during volatile periods. Kodres (1993) used a maximum likelihood approach and $GARCH$ model with censored normal tails to test the unbiasedness hypothesis[2] on foreign exchange futures market.

Levy and Yagil (2006) compared six alternative models of the return-generating process (RGP). The models included a $GARCH$ (1,1) process by the MLE algorithm; $GARCH$ with censored normal (Chou (1999)) by the MLE algorithm; GARCH with truncated normal (Chou (1999)) by the MLE algorithm; $GARCH$(1,1) by the expectation-maximiz -ation (EM) algorithm (Dempster et al. (1977)); the adjusted version of dummy-variables model (Park (2000)) by the MLE algorithm; and the near-limit model [3](Levy and Yagil (2005)) by the MLE algorithm. The authors used the mean square error (MSE) and the MSE coefficient of variation as ranking criteria. The better performance of the near-limit model shows that it is needed to include the clusters around the limits for building a more acceptable model. Wei and Chiang (1997) used the generalized method of moments (GMM) to estimate the mean, variance, and covariance of doubly truncated daily prices. This chapter proposes a $GARCH$(1,1) model with CCN

[2] The hypothesis assumes that the futures rate is an unbiased predictor for the futures spot rate.

[3]A comparison between the near-limit model and $GARCH$ with CCN tails is of interest. We hope to present the comparison in future research.

tails ($GARCHCCN$) using the MLE algorithm and compares the performance among a $GARCH$(1,1), a $GARCH$(1,1) with truncated normal ($GARCHTN$), a $GARCH$(1,1) with censored normal ($GARCHCN$), and $GARCHCCN$ [4].

The rest of this chapter is arranged as follows. Section 2.2 introduces the mathematical models and demonstrates the statistical properties of truncated, censored, and clustered censored $GARCH$ under Gaussian using Monte Carlo simulations. Section 2.3 presents the empirical evidence of 5 stocks from the $TSEC$ Weighted Index, 5 stocks from the SSE Composite Index, 5 stocks from the $KOSPI$ Index, and 5 stocks from the CAC 40 by using $GARCH$(1,1), $GARCHCN$, $GARCHTN$, and $GARCHCCN$. Then, conclusions are made based on the results in Sections 2.2 and 2.3.

2.2 Mathematical models and Monte Carlo Simulations

The mathematical set-ups for each model contain the same time varying conditional variance generating process given as,

$$h_t = \kappa + (\alpha_1 h_{t-1} + ... + \alpha_p h_{t-p}) + (\beta_1 u_{t-1}^2 + ... + \beta_q u_{t-q}^2) \tag{2.2.1}$$

The return for any time period t is denoted as u_t. $u_t \sim N(0, h_t)$ in $GARCH(p,q)$[5]; $u_t \sim CN((0; h_t), Lower, Upper)$ in $GARCHCN(p,q)$; $u_t \sim TN((0; h_t), Lower, Upper)$ in $GARCHTN(p,q)$; and $u_t \sim CCN((0; h_t; l_1; r_1; m_1; m_2), Lower, Upper)$ in $GARCHCCN(p,q)$.

It have been discussed in last chapter that the empirical data with limits tend to be clustered censored distributions. Clustered censored distributions contain special cases, e.g., censored or truncated distributions. In addition, we will justify the fact that $GARCHCCN$ provides a better goodness of fit for financial returns with bounds in Empirical Evidence section in this chapter. Thus, it is necessary to discuss the outcomes of using wrong models by using Monte Carlo simulations. We use $p = 1$ and $q = 1$ as primary models of $GARCH(p,q)$, $GARCHCN(p,q)$, $GARCHTN(p,q)$, and $GARCHCCN(p,q)$.

In order to investigate the biases (the absolute differences between the true values and the estimates) of parameters estimated by using $GARCH$ or the real model in simulations of $GARCHCN$, $GARCHTN$, and $GARCHCCN$ models, Monte Carlo simulations

[4] To make sure the estimates give a global optimum of log likelihood value, we use different initial values when using MLE, as well as plotting the curves of the log likelihood with respect of changes of each parameter based on the obtained optimal set of estimates.

[5] To save space, $GARCH$ is abbreviated as G; $GARCHCN$ is as GCN; $GARCHTN$ is as GTN; and $GARCHCCN$ is denoted as $GCCN$ in table H.0.3.

presented in table F.0.1 are used. Ng and Lam (2006) found that the correlation of conditional variances of estimated model between the limited samples and the large samples (e.g., 3000) is not less than the high value of 0.90 if sample size is more than 1000. Thus, at least 1000 observations are recommended for $GARCH$. Yet a set of parameter estimates for κ, α, and β is considered efficient if p-value of each parameter is not greater than 0.01. In table G.0.2, Monte Carlo simulations of $GARCH$ model give parameter estimates for κ, α, and β, with a confidence interval greater than 99% if data size is at least 1400, which is 400 more than the number suggested by Ng and Lam (2006). To have efficient set of parameter estimates for κ, α, and β, at least 1800 data are required in $GARCHCCN$ simulations (table G.0.3). Estimate biases are investigated by Monte Carlo simulations that have 5000 data in each simulation, and the simulations are repeated 1000 times.

For each parameter, there are 1000 estimated values and 1000 standard deviations derived from Hessian Matrix. The mean and standard deviation of the 1000 estimated values of each parameter are attained. This value of standard deviation of the parameter is denoted as the S-standard deviation. The mean of every standard deviation group derived from Hessian Matrix is represented by the MH-standard deviation. For example, the two standard deviations for each estimated parameter in $GARCHCN$ simulations are listed in table F.0.2: the one on the right of the slash embedded in the parenthesis under an estimated parameter is the related S-standard deviation, and the one on the left is the corresponding MH-standard deviation. Monte Carlo simulations of $GARCHCN$ have different bounds, e.g., $[-2.5, 2.5]$, $[-3, 3]$, $[-3.5, 3.5]$, $[-4, 4]$, and $[-5, 5]$. Moreover, to decide $p - value$ of the estimated parameter, the S-standard deviation is used rather than the MH-standard deviation because table G.0.1 indicates that when data size is small, the MH-standard deviation converges to the related S-standard deviation as repetition number increases [6]. Roughly speaking, the two approximations of standard deviation are similar. In Empirical Evidence, we obtain standard error of each parameter estimate from Hessian matrix and these standard errors are used to calculate the p-value of each estimate. In practice, the S-standard deviation and MH-standard deviation both are not feasible because we only have one sample. In this case, the two bootstrapping algorithms in Tibshirani (1996)[7] - bootstrap pairs sampling algorithm and bootstrap residual sampling algorithm, can be used.

[6] Differences between MH-standard deviation and S-standard deviation under some circumstances were discussed in many past research, e.g., Harding et al (2014) and Tibshirani (1996). Two factors determine the precision of the parameter estimates, the population's variability and sample size. Population's variability and the S-standard deviation are positively related. The measure of S-standard error is inversely proportional to a function of sample size, often $\sqrt{T}$. T is the sample size.

[7] Tibshirani (1996) compared the delta method based on the Hessian, bootstrap estimators, and the "sandwich" estimator. He demonstrated that the two bootstrap methods perform best. The author indicated in the paper that these two methods capture variability partly due to the choice of starting weights.

Tables F.0.2 and F.0.3 indicate that the biases of the parameters estimated by using $GARCH$ in $GARCHCN$ simulations are smaller than those in $GARCHTN$ simulations when underlying parameters and bounds are the same. When the bounds are $[-2, 2]$, the upward bias of κ is 7.2%, the downward bias of α is 1.35%, and the upward bias of β is 0.06% by using $GARCHCN$ in $GARCHCN$ simulations, while the upward bias of κ is 6.6%, the downward bias of α is 1.36%, and the downward bias of β is 68.86% by $GARCH$. The biases of theses two models are almost identical. BIC values of $GARCHCN$ are greater than those of $GARCH$. Choosing true model based on BIC values might be misleading.

On the contrary, in $GARCHTN$ simulations with the same underlying parameters and bounds as mentioned above, the true model exhibits an upward bias of 46.53% in κ, a downward bias of 10.58% in α, and an upward bias of 11.13% in β, while $GARCH$ has a greater upward bias of 147.87% in κ, a greater downward bias of 35.93% in α, and a greater downward bias of 46% in β. The BIC value of the true model is lower than that of $GARCH$. These facts coincide with the simulations in previous chapter, in which the population standard deviation of CN model is closer to the true standard deviation than that of TN (figure D.1).

Moreover, the BIC of the real model is lower than that of $GARCH$ in $GARCHCCN$ simulations as long as κ, α, β, and clustering coefficients are all statistically significant with a confidence interval of 99% (table F.0.4). As the BIC values of the fitted $GARCHCCN$ and $GARCH$ move closer to each other, the estimates of κ, α, and β using $GARCHCCN$ converge to those using $GARCH$. The biases of $GARCH$ estimates decrease when bounds change from $[-3, 3]$ to $[-4, 4]$ (rows 1 and 2 in table F.0.4). Specifically, the first row has an upward bias of 561.66% in κ, a downward bias of 0.52% in α, and a downward bias of 83.72% in β by $GARCH$, while there are a lower upward bias of 399.67% in κ, a downward bias of 0.58% in α, and a smaller downward bias of 40.73% in β by $GARCHCCN$. The second row has an upward bias of 403.67% in κ, an upward bias of 6.03% in α, and a downward bias of 83% in β by $GARCH$, while there are a much smaller upward bias of 69.67% in κ, an upward bias of 3% in α, and a smaller downward bias of 35% in β by $GARCHCCN$. However, the biases of $GARCH$ estimates increase as bounds increase from $[-4, 4]$ in the second row to $[-5, 5]$ in the third row. In rows 3-5, the biases of $GARCH$ estimates decline as bounds increase. This consequence of changes of the estimated biases matches the concave down '$variance - b$' curve in the first chapter.

The S-standard deviations and MH-standard deviations are similar if domains are $[-3, 3]$, $[-4, 4]$, and $[-5, 5]$ and when l_1 and r_1 are 0.6, m_1 is 0.85, and m_2 is -0.85 as shown in rows 6 to 8; or when l_1 and r_1 are 0.6, m_1 is 0.55, and m_2 is -0.55 (rows $11 - 13$ in table F.0.4). The comparisons of rows 6 and 11, rows 7 and 12, rows 8 and 13, rows 9 and 14, and rows 10 and 15 suggest that with the same bounds, the $GARCHCCN$ model with a smaller m_1 and greater m_2 still have the estimates of clustering coefficients statistically significant with a confidence interval greater or equal to 95%, while with the same significance level, the estimates of clustering coefficients of the $GARCHCCN$ simulations with a grater m_1 and smaller m_2 are not statistically significant. As a matter of fact, the clusters can be ignored.

Similarly, the comparisons between rows 1 and 6, between rows 2 and 7, between rows 3 and 8, between rows 4 and 9, and between rows 5 and 10 show that the $GARCHCCN$ with lower clustering rates still have clustering coefficient estimates that are statistically significant with a confidence interval greater or equal to 95% while its counterparts closely resemble the fitted $GARCH$ model. Given these points, if the BIC values of $GARCHCCN$ and $GARCH$ are fairly close according the rules in E.0.2, the clustering coefficients are negligible. These findings explain why Korean and Chinese stocks usually have lower clustering rates than Taiwanese stocks in table H.0.3. Even though the bounds of Korean and Chinese stocks are wider than those of Taiwanese ones, the clustering coefficients may be statistically significant with a confidence interval greater or equal to 95% when the clustering rates are lower and the clustering ranges are wider. Nevertheless, even when the clusters can be ignored, the estimated clustering rates are statistically significant with a confidence interval of 95% (table F.0.4).

There are large parameter estimation biases in percentage term when bounds are about twice of the underlying standard deviation and large biases in clustering coefficients (not statistically significant with a significant level of 10%) when bounds are over 6 or 7 of the underlying standard deviation in Monte Carlo simulations of $GARCHCCN$ - yet our empirical evidence next section show that small relative bounds causing large estimation biases or large relative bounds resulting in large standard error for estimated clustering coefficients are not likely to occur. The relative bounds, the ratios between lower/upper bounds and the underlying standard deviation, tend to be larger than five in table I.0.1. Estimates are all statistically significant with a confidence interval of 90%. It would be better if we can define a circumstance that $GARCHCCN$ gives an unbiased set of parameters. The circumstance can be a combination of restrictions on relative bounds, clustering coefficients, and clustering rates. We are looking forward to having this part of research in future. In addition, the empirical evidence in next section illustrate the superiority of $GARCHCCN$ over other models by using BIC values, in-sample VaRs, and out-of-sample VaRs.

2.3 Empirical Evidence

2.3.1 Fitted Models: 5 Taiwanese, 5 Chinese, 5 Korean, and 5 French stocks

Table H.0.2 lists the data used in this section. There are obvious differences in the κ, α, and β estimated by using $GARCHCCN$ compared to those using other models. The

κ's, α's, and β's estimated by using $GARCH$, $GARCHTN$, and $GARCHCN$ are very similar in each stock (table H.0.3). The κ of the fitted $GARCH$ is about half of that of $GARCHCCN$ in ChinaTrust, Fubon, Formosa Petrochemical Corp, Inner Mongolia Baotou, Samsung, Enex, and LVMH. The difference of β's between the fitted $GARCH$ and $GARCHCCN$ models is 0.0210 out of the β of the fitted $GARCHCCN$ of 0.0263 in Acer, 0.0216 out of 0.0314 in ChinaTrust, 0.0269 out of 0.0447 in Clevo, 0.0206 out of 0.0280 in Fubon, 0.0203 out of 0.0203 in Formosa Petrochemical Corp, 0.0305 out of 0.0301 in TsingHuaTongFang, 0.0265 out of 0.0272 in GDPower, 0.0470 out of 0.0216 in China Merchant Banks, 0.0386 out of 0.0459 in ShangHai International Airport, 0.0188 out of 0.0384 in Posco, and 0.0216 out of 0.0468 in Danone.

In addition, the clustering rates, the left and right clustering coefficients of two stocks from the same composite index can be very different. The clustering coefficient, m_1 is in [0,1]; and m_2 is in [-1,0] in every stock except Acer, Clevo, China Merchants Bank, and BNP. The values of m_1 and m_2 are symmetric if $m_1 = -m_2$. If $m_1 < -m_2$, there are steeper left clusters; conversely, there are steeper right clusters. Steeper right clusters are observed in Acer, ChinaTrust, Clevo, Fubon, TsingHuaTongFang, China Merchants Bank, and Gemalto.

The rates l_1 and r_1 are different in stocks from the same composite index. These rates of stocks in the $TSEC$ Weighted Index are usually higher than those in other indices. The values of l_1 and r_1 are close to 0.8 in all Taiwanese stocks except Formosa Petrochemical Corp. Instead, for most Chinese, Korean, and French stocks, the values are usually close to 0.5 or lower. Comparing l_1 to r_1, we find that Acer, ChinaTrust, Clevo, Fubon, TsingHuaTongFang, GDPower, Inner Mongolia Baotou, China Merchants Bank, ShangHai International Airport, Naver, Samsung, Willbes, Enex, Posco, and Danone have bigger right clustering rates. l_1, r_1, m_1, and m_2 estimates are statistically significant with a 99.9% confidence interval in every stock, only except the m_1's in ChinaTrust with a $p-value$ of 1.84% and Gemalto with a p-value of 4.23%. To sum up, clusters in the 20 stocks are not negligible.

In table I.0.1, the notation of σ is the solution of x (which represents the converging value of the underlying conditional standard deviation) in the equation $x^2 = \kappa + \alpha * x^2 + \beta * ccn_{2nd}((0; x^2; l_1; r_1; m_1; m_2), Lower, Upper)$, while the value $\sqrt{\kappa/(1-\alpha-\beta)}$ usually used in $GARCH$ is also displayed. The lower value of $\sqrt{\kappa/(1-\alpha-\beta)}$, the convergent value of population standard deviation, compared to σ in each stock only except GDPower suggests that in general, price limits decrease volatility.

The relative bounds are $Lower/\sigma$ and $Upper/\sigma$. GDPower, Shanghai International Airport, Samsung, Willbes, Enex, Posco, and Danone have $-Lower/\sigma$ and $Upper/\sigma$ greater than 8. The clustering rates of these stocks (except Enex) are in a domain of $[0.3, 0.4]$.

This is expected because in order to have clusters that are not negligible, the ranges of clusters should be wider if relative bounds are comparably large (this corresponds to the conclusions based on table F.0.4 in Section 2.2).

Comparing GDPower with ShangHai International Airport, we observe that the m_2 of GDPower, -0.4375, has greater magnitude than that of ShangHai International Airport, -0.2847. In addition, the relative bounds of GDPower are wider. With almost identical Ω and pm, the population standard deviation in $GDPower$ is greater.

Comparing GDPower with Enex, we found that the clustering rates of Enex are both around 0.75 while those of GDPower are about 0.3. The Ω and pm of Enex both are equal to 1. The *cdf* of the two sides of clusters is arbitrarily equal to 0 in Enex. Nevertheless, in GDPower, the *cdf* of clusters is 0.0352. In conclusion, higher population standard deviation of GDPower compared to the underlying standard deviation is caused by a mixture of comparatively larger bounds and greater portions at clusters about bounds.

Moreover, in table I.0.1, $\Omega \in [1, 1.0917]$ and $pm \in [0.8931, 1]$. A value of pm arbitrarily close to 1 does not mean that the clusters are negligible because of heteroscedasticity in the fitted models. The Ω and pm values, as well as the underlying conditional variance, are changing over time.

2.3.2 In-sample VaR Estimates

The estimated parameters in section 2.3.1 are used to calculate the one-day-ahead VaRs for given p's that are 10%, 5%, and 2.5%. Table I.0.2 contains the failure ratio, the $Kupiec$ likelihood ratio, and $E(shortfall^2)$. If $u_t < -VaR_t$, in which VaR_t is the p VaR at t, there is a failure/violation. The failure ratio is conducted as x/T, where x is the number of violations for a significant level equal to p; and T is the total number of observations.

$Kupiec$ LR test is useful because it is rarely the case that the failure ratio is exactly equal to p. The test measures the Proportion of Failures (POF) and checks the consistency of the number of violations with p, under null hypothesis that the model is correct by assuming the number of violations follows the binomial distribution. The test statistics are given by,

$$LR_{POF} = -2log\left(\frac{p^x * (1-p)^{T-x}}{\left(\frac{x}{T}\right)^x \left[1-\left(\frac{x}{T}\right)^{T-x}\right]}\right) \sim \chi^2(1) \tag{2.3.1}$$

If the $p-value$ of this test is smaller than a chosen threshold value c, called the significance level of the test, the hypothesis is rejected and the model is considered to be inaccurate for the data.

$E(shortfall^2)$ measures the usefulness of the fitted model to lower potential loss. The smaller the value is, the better the fitted model is. For each date t, $shortfall_t = u_t + VaR_t$, if there is a failure at t. Otherwise, $shortfall_t$ is equal to 0. $E(shortfall^2)$ is the mean of $shortfall_t^2$ that is equal to the sum of $shortfall_t^2$ over all the dates divided by x.

In R_{c_1}, c_1 is the $p - value$. For each stock, a model is rejected at a significance level c as long as it has any (R_{c_1}) mark and $c_1 \leq c$ because if a model is adequate for a financial time series, its LR test score for any of the three p's should not exceed the related critical value. The critical values of $\chi^2(1)$ distribution are 3.841 for $c_1 = 0.05$, 5.024 for $c_1 = 0.025$, and 6.635 for $c_1 = 0.01$. In table I.0.2, no R sign is displayed if LR test is smaller than 3.841. There is a $R_{0.05}$ if the LR test is in $[3.841, 5.024)$, $R_{0.025}$ if the LR test is in $[5.024, 6.635)$, and $R_{0.01}$ if the LR test is in $[6.635, \infty)$.

$GARCHCCN$ is not rejected as a good model for each stock with c equal to 5%. Nonetheless, $GARCH$, $GARCHCN$, and $GARCHTN$ are rejected with a significance level of 5% in all stocks except Acer. The in-sample $VaRs$ of each time period are plotted in figures I.1a, I.1b, I.1c, I.1d, I.2a, I.2b, I.2c, I.2d, I.3a, I.3b, I.3c, I.3d, I.4a, I.4b, I.4c, I.4d, I.5a, I.5b, I.5c, and I.5d. The minus $VaRs$ of $GARCHCCN$ are inside of the bounds and display POF that is fairly close to the selected p in each stock.

2.3.3 Out-of-sample VaRs

Tables G.0.2 and G.0.3 imply that $GARCH$ model needs more than 1400 data to find a stable and efficient estimation of parameters and $GARCHCCN$ model requires a minimum amount of 1800. Therefore, data with more than 1800 returns are used to find the out-of-sample $VaRs$, where the model is estimated on the returns over the preceding $T - 400$ days, $\{u\}_{t^*-(T-400)+1}^{t^*}$, and the VaR forecast is made for some period $\{t^* + 1, ..., t^* + s\}$. T is the total number of data. s is the forecast time horizon and it is assumed to be $s = 1$ day. $t^* = T - 400, T - 399, ..., T - 1$. In past literature, it is debated that out-of-sample $VaRs$ should be favourable to the in-sample forecasts for model selection.

Moreover, $Christoffersen's$ Interval Forecast Test is added in this section to check the existence of violation clusters. $Christoffersen's$ Interval Forecast Test is probably the most well-known test for conditional coverage and it has been discussed in Jorion (2001), Campbell (2005), Dowd (2006) and Christoffersen (1998). It tests whether the exception of each day's outcome is based on the violation of the previous day. The test is carried out by describing an indicator that has a value of 1 if the return exhibits a loss greater than the p (we use the same p's as in in-sample $VaRs$, which are 0.1, 0.05, and 0.025) VaR_t and a value of 0 otherwise.

$$I_t = \begin{cases} 1 & \text{if violation occurs} \\ 0 & \text{else} \end{cases}$$

Then let n_{ij} be the indicator that condition i occurs on the previous day and j on the current day. The outcomes can be displaced in a 2×2 contingency table:

	$I_{t-1} = 0$	$I_{t-1} = 1$	
$I_t = 0$	n_{00}	n_{10}	
$I_t = 1$	n_{01}	n_{11}	
	$n_{00} + n_{01}$	$n_{10} + n_{11}$	

Let π_i be the probability that an exception occurs given the previous day's indicator is i. Therefore, $\pi_0 = n_{01}/(n_{01} + n_{00})$ and $\pi_1 = n_{11}/(n_{11} + n_{10})$. Let π be the probability that an exception occurs disregarding of the indicator of the previous day and so $\pi = (n_{01} + n_{11})/(n_{01} + n_{00} + n_{11} + n_{10})$.

The model is not rejected as a good model if the null hypothesis, the likelihood that an exception occurs is independent of whether or not an exception occurs on the previous day, is not rejected by the test defined by the following formula:

$$LR_{ind} = -2 * log \left(\frac{(1-\pi)^{n_{01}+n_{00}} \pi^{n_{11}+n_{10}}}{(1-\pi_0)^{n_{00}} \pi_0^{n_{01}} (1-\pi_1)^{n_{10}} \pi_0^{n_{11}}} \right) \tag{2.3.2}$$

By combining this test with the *Kupiec* test, we have a joint test of failure rate and independence of exceptions, e.g., conditional coverage:
$LR_{cc} = LR_{ind} + LR_{POF}$
This test statistics is $\chi^2(2)$ since there are two independent LR-statistics in the test.

In table H.0.1, *GARCHCCN* has better *Kupiec* LR test and LR_{cc} independent test in Acer, Clevo, Fubon, Formosa Petrochemical Corp, TsingHuaTongFang, GDPower, ShangHai International Airport, Naver, Willbes, Enex, Danone, Gemalto, and Vallourec; and comparable performance in the rest of the stocks. In addition, the out-of-sample *VaRs* for the last 400 periods of each stock are plotted in figures H.1a, H.1b, H.1c, H.1d, H.2a, H.2b, H.2c, H.2d, H.3a, H.3b, H.3c, H.3d, H.4a, H.4b, H.4c, H.4d,H.5a, H.5b, H.5c, and H.5d.

2.4 Conclusions

In this chapter, the in-sample and out-of-sample *VaRs* are presented to convey strong support for *GARCHCCN* when compared with *GARCH*, *GARCHCN*, and *GARCHTN* in evaluating risks for the doubly bounded data with either ostensible or hard to observed clusters. The fitted $GARCHCCN$ has the smallest BIC for each stock. The lowest $Kupiec$ test and lowest $E(shortfall^2)$ of in-sample $VaRs$ in 20 stocks indicate $GARCHCCN$ can have more precise estimations of one-day-ahead in-sample $VaRs$ and may help to lower financial losses while the other three models are deemed as inaccurate with a significance level of 0.05 in 19 out 20 stocks. Furthermore, the out-of-sample $Kupiec$ and $Christoffersen's$ tests show that clustered censored property can explain why out-of-sample VaR tests of the other models exhibit violation clusters. Empirical evidence also show that the relative bounds are mostly over five and price limits tend to make population standard deviation lower than underlying standard deviation. However, this does not mean increasing bounds will lead to larger variance because we found that as bounds change, the changes of clustering rates and clustering coefficients become intertwined, e.g., larger relative bounds accompanied with comparably smaller clustering rates and flatter clusters.

It is hard to say whether $GARCHCCN$ has better LR_{cc} test for p equal to 0.1 or other p's. For instance, compared to other three models, $GARCHCCN$ has better LR_{cc} when p equal to 0.1, but comparable LR_{cc} values when p equal to other two values in Fubon, Formosa Petrochemical Corp, and TsingHuaTongFang. This fact makes sense because when p is either 0.05 or 0.025, the variables between the lower bound and the minus p VaR of the fitted $GARCHCCN$ may just be censored values (in Chapter 3, we call them mapped values) of variables generated from a $GARCH$ model. In this case, the p VaRs for each fitted models are very close to each other. At the same time, the better out-of-sample VaR forecast when p is equal to 0.1 suggests that price limits distort the distribution of a financial time series at a *cdf* value close to 0.1. $GARCHCCN$ is more suitable than other models to detect this distortion. On the other hand, in Willbes, it is shown that $GARCHCCN$ can also exhibit better out-of-sample VaR forecast when p is 0.025. In fact, $GARCHCCN$ outperforms other three models under different circumstances.

However, $GARCHCCN$ is rejected as a good model with a confidence interval of 99.5% in ChinaTrust, Clevo, Inner Mongolia BaoTou, and GDPower; of 95% in Fubon and Posco; and of 90% in LVMH according to the LR_{cc} values. It was demonstrated that $GARCH$ with heavy tailed distributions, e.g., Student-t, outperform $GARCH$ with a normal error distribution when there is no bound on financial data. Consequently, I examine whether better out-of-sample VaR estimate can be achieved by using the combination of clustered censored property and heavy tail distributions, such as $Student-t$ and GED in next chapter.

Likewise, $TGARCH$ and $EGARCH$ (Li et al. (1996), Rabemananjara and Zakoïan (1993), and Zakoïan (1994)) with clustered censored distributions can be implemented to include the leverage effect between returns and variance. In addition, a model may be proposed in future to capture the spillover effects from unrealized return today to tomorrow's volatility and return. Through this model, policy makers can find an optimal set of bounds that balances the negative effects of price limits, e.g., volatility spillovers (a consequent of an extremely large volatility is large fluctuations over several subsequent days), and the positive effects, e.g., population standard deviation lower than underlying standard deviation.

Finding the comovements of financial returns is of great practical importance because the covariance of assets in a portfolio affects the optimal hedging positions. Asset pricing, risk management, and portfolio allocation are closely related to the correlations among different financial assets (Bollerslev, Engle, and Wooldridge (1988), Ng (1991), and Hansson and Hördahl (1998)). As a result, multivariate cluster censored models will be evaluated.

Chapter 3

Clustered Censored GARCH with Student-t and Spillovers

3.1 Introduction

The modern empirical finance contains two main approaches, namely the unconditional and the conditional approaches. The unconditional approach using the Gaussian distribution was the first to be considered but numerous papers, e.g., Mandebrot (1963), Fama (1965), Blatterberg and Gonedes (1974), Box and Tiao (1962), Mittnik and Rachev (1993), Shephard (1996), Rydberg (2000), Mittnik, Rachev, and Paolella (1998), Mittnik and Rachev (2000), demonstrated the returns of financial assets have fatter tails and more peaked about the center than that predicted by a Gaussian distribution. In Chapter 1, we have found that under Gaussian, the adding of clustered censored property improved data fitting for 20 stocks. In particular, CCN has sharper peak than CN, TN, and normal, e.g., figures E.2b and E.2c. The clusters about the lower and upper bounds can be captured by using different clustering ranges and shapes. Since heavy tailed distributions, e.g., Student-t distribution, outperform Gaussian distribution in unlimited financial assets using the unconditional approach, an extension of clustered censored property to heavy tailed distributions can be proposed to describe the unconditional distribution of financial returns.

On the other hand, the conditional approach became common in empirical finance. One of the predominant models is developed by Engle (1982) and latter Bollerslev (1986). In its standard form GARCH models have normal conditional distribution of assets returns. However, for many financial returns, the error series normalized by the conditional variance generating process may still be leptokurtic. Bollerslev (1987), Beine, Laurent, and Lecourt (2002) among others used $Student-t$ distribution. Nelson (1991) and Kaiser (1996) recommended GED. Both $Student-t$ and GED have been investigated by Hsieh (1989).

The Laplace distribution was discussed in Granger and Ding (1995). The stable Paretian distributions were evaluated in Liu and Brorsen (1995), Panorska et al. (1995), and Mittnik and Paolella (2003). Curto et al. (2007) found that a GARCH model with Student-t outperforms the Normal and stable Paretian distributions using the out-of-sample density forecasts for the daily returns of the US, German, and Portuguese main stock market indexes (to have a comparison of large and small economies). Therefore, $GARCH$ models with heavy tails tend to outperform $GARCH$ with a normal error distribution in boundless financial time series. Similarly, under price limits $GARCH$ with a clustered censored heavy tailed distribution tends to outperform $GARCHCCN$.

VaR emerged as a suitable measure of risk and it became substantially popular due to its simplicity. Despite the lack of complexity and sub-additivity in VaR (Cheng, Liu, and Wang (2004)), it has been recommended by numerous international financial institutes, e.g., the Bank for International Settlements and the SEC. An extension of clustered censored property to $Student-t$ is worth doing since the suggested $GARCHCCN$ even though outperforms $GARCH$, $GARCHCN$, and $GARCHTN$, was rejected as an appropriate model for seven out of twenty stocks with a significance level of 10% in Chapter 2. The out-of-sample VaR forecasts are compared among alternative conditional distributional models for seven stocks.

The rest of this chapter is organized as follows. Section 3.2 introduces clustered censored $Student-t$ in both exponential and polynomial forms. Section 3.3 demonstrates the performance of the out-of-sample VaR estimate of $GARCH$ with $Student-t$ [1]innovations, and clustered censored $Student-t$ in exponential and polynomial forms among seven stocks. Similarly, the six moments, including mean, variance, skewness, kurtosis, $E(u_t u_{t-1})$, and $E(u_t^2 u_{t-1}^2)$, simulated by fitted models are compared with those of data in order to select the preferred conditional distributional model from a set of candidate models. Section 3.4 concludes and presents a direction of future research that emphasizes on spillover effects. Section 3.5 demonstrates both group and one-to-one mapping rules as two approaches to test spillover effects.

3.2 Clustered Censored Student-t in exponential and polynomial forms

Let $v > 2$. The *pdf* of standardized $Student-t$ with a degree of freedom, v, at value x is shown as

$$pdf_{stdtst}(x;v) = \frac{\Gamma(\frac{v+1}{2})}{\Gamma(\frac{v}{2})\sqrt{\pi(v-2)}}(1+\frac{x^2}{v-2})^{-\frac{v+1}{2}} \tag{3.2.1}$$

[1]The model and moments of a clustered censored GED are illustrated in Appendix K. This chapter omits the empirical performance of $GARCH$ with GED tails.

A generalized $Student-t$ distribution has a location parameter of μ, a scale parameter of σ, and a degree of freedom of v. The *pdf* is

$$\begin{aligned} pdf_{gt}(x;\mu,\sigma,v) &= \frac{\Gamma(\frac{v+1}{2})}{\sigma\Gamma(\frac{v}{2})\sqrt{\pi(v-2)}}(1+\frac{(x-\mu)^2}{(v-2)\sigma^2})^{-\frac{v+1}{2}} \\ &= \frac{pdf_{stdtst}(\frac{x-\mu}{\sigma};v)}{\sigma} \end{aligned} \tag{3.2.2}$$

Similar to CCN model, the *pdf* of a clustered censored generalized $Student-t$ can be divided into three segments. Let $parameters = (\mu;\sigma^2;v;l_1;r_1;m_1;m_2)$. $Lower$ is the lower bound; and $Upper$ is the upper bound. Let $a_1 = \mu + l_1 * (Lower - \mu)$ and $b_1 = \mu + r_1 * (Upper - \mu)$. $A = pdf_{gt}(a_1;\mu,\sigma,v)$ and $B = pdf_{gt}(b_1;\mu,\sigma,v)$. The value of $\Omega_{ccgt}(parameters, Lower, Upper)$ is the sum of the following three values as shown in equations J.0.30, J.0.27, J.0.34, J.0.40, and J.0.35.

$$\begin{aligned} \Omega_{ccgt}(parameters, Lower, Upper) = L_{0_{ccgt}}&(parameters, Lower, Upper) \\ &+ M_{0_{ccgt}}(parameters, Lower, Upper) \\ &+ R_{0_{ccgt}}(parameters, Lower, Upper) \end{aligned} \tag{3.2.3}$$

Therefore, by using equations J.0.31, J.0.26, J.0.36, J.0.30, J.0.27, J.0.33, J.0.39, and J.0.35, the *pdf* and *cdf* functions are written as

$$pdf_{ccgt}(x) = \begin{cases} \frac{pdf_{gt}(x;\mu,\sigma,v)}{\Omega_{ccgt}(parameters,Lower,Upper)} & \text{if} a_1 \le x \le b_1 \\ \frac{exp(m_1(x-a_1))A}{\Omega_{ccgt}(parameters,Lower,Upper)} & \text{if} Lower \le x \le a_1 \\ \frac{exp(m_2(x-b_1))B}{\Omega_{ccgt}(parameters,Lower,Upper)} & \text{if} b_1 \le x \le Upper \\ 0 & \text{else} \end{cases}$$

$$cdf_{ccgt}(x) = \left\{ \begin{array}{ll} 0 & \text{if} x < Lower \\ \frac{L_{0_{ccgt}}(x,parameters,Lower,Upper)}{\Omega_{ccgt}(parameters,Lower,Upper)} & \text{if} Lower \le x \le a_1 \\ \frac{L_{0_{ccgt}}+M_{0_{ccgt}}(x,parameters,Lower,Upper)}{\Omega_{ccgt}(parameters,Lower,Upper)} & \text{if} a_1 \le x \le b_1 \\ \frac{L_{0_{ccgt}}+M_{0_{ccgt}}+R_{0_{ccgt}}(x,parameters,Lower,Upper)}{\Omega_{ccgt}(parameters,Lower,Upper)} & \text{if} b_1 \le x \le Upper \\ 1 & \text{if} x > Upper \end{array} \right\}$$

(Notes: pdf_{ccgt}(x,parameters,Lower,Upper), cdf_{ccgt}(x,parameters,Lower,Upper), $L_{0_{ccgt}}$ (parameters,Lower,Upper), $M_{0_{ccgt}}$(parameters,Lower,Upper), and $R_{0_{ccgt}}$(parameters,Lo -wer,Upper) are shortened as $pdf_{ccgt}(x)$, $cdf_{ccgt}(x)$, $L_{0_{ccgt}}$, $M_{0_{ccgt}}$, and $R_{0_{ccgt}}$ in the equations of pdf_{ccgt} and cdf_{ccgt}.)

The mean, variance, skewness, and kurtosis are derived in equations J.0.42, J.0.44, J.0.46, and J.0.48. During the research, I have found a polynomial clustered form. The reasons for having a new form of clusters are first, the concern about the shapes of clusters, e.g., whether exponential functions are too steep to define the clusters (for example, the clustering spike at upper bounds in figures E.3c and E.3d are much higher than the clusters demonstrated in the histograms); second, standard deviations of estimates using $GARCHCCST$ can be too big (which might be caused by the overly steep exponential form of clusters), e.g., Clevo, GDPower, and Lotes (table L.0.3). Let $parameters = (\mu; \sigma^2; v; l_1; r_1; \rho_1; \rho_2)$

$$i \in \{0, 1, 2, 3, 4\}$$

If $x \in [Lower, a_1]$,

1. and $\rho_1+i+1 \neq 0$, $L_{i_{ccgt_p}}(x, parameters, Lower, Upper) = A\frac{(a_1-Lower+1)^{\rho_1+i+1}-(a_1-x+1)^{\rho_1+i+1}}{\rho_1+i+1}$.
2. and $\rho_1 + i + 1 = 0$, $L_{i_{ccgt_p}}(x, parameters, Lower, Upper) = A(log(a_1 - Lower + 1) - log(a_1 - x + 1))$.

If $x \in [b_1, Upper]$,

1. and $\rho_2 + i + 1 \neq 0$, $R_{i_{ccgt_p}}(x, parameters, Lower, Upper) = B\frac{(x-b_1+1)^{\rho_2+i+1}}{\rho_2+i+1}$.
2. and $\rho_2 + i + 1 = 0$, $R_{i_{ccgt_p}}(x, parameters, Lower, Upper) = B * log(x - b_1 + 1)$.

Let $x \in [a_1, b_1]$, $M_{i_{ccgt_p}}(x, parameters, Lower, Upper) = M_{i_{ccgt}}(x, parameters, Lower, Upper)$.

$$\begin{aligned}\Omega_{ccgt_p}(parameters, Lower, Upper) = {} & L_{0_{ccgt_p}}(a_1, parameters, Lower, Upper) \\ & + R_{0_{ccgt_p}}(Upper, parameters, Lower, Upper) \\ & + M_{0_{ccgt_p}}(b_1, parameters, Lower, Upper)\end{aligned} \tag{3.2.4}$$

The pdf and cdf are defined as follows:

$$pdf_{ccgt_p}(x) = \begin{cases} \frac{pdf_{gt}(x;\mu,\sigma,v)}{\Omega_{ccgt_p}(parameters,Lower,Upper)} & \text{if} a_1 \leq x \leq b_1 \\ \frac{(a_1-x+1)^{\rho_1}A}{\Omega_{ccgt_p}(parameters,Lower,Upper)} & \text{if} Lower \leq x \leq a_1 \\ \frac{(x-b_1+1)^{\rho_2}B}{\Omega_{ccgt_p}(parameters,Lower,Upper)} & \text{if} b_1 \leq x \leq Upper \\ 0 & \text{else} \end{cases}$$

$$cdf_{ccgt_p}(x) = \left\{ \begin{array}{ll} 0 & \text{if} x < Lower \\ \frac{L_{0_{ccgt_p}}(x,parameters,Lower,Upper)}{\Omega_{ccgt_p}(parameters,Lower,Upper)} & \text{if} Lower \leq x \leq a_1 \\ \frac{L_{0_{ccgt_p}}+M_{0_{ccgt_p}}(x,parameters,Lower,Upper)}{\Omega_{ccgt_p}(parameters,Lower,Upper)} & \text{if} a_1 \leq x \leq b_1 \\ \frac{L_{0_{ccgt_p}}+M_{0_{ccgt_p}}+R_{0_{ccgt_p}}(x,parameters,Lower,Upper)}{\Omega_{ccgt_p}(parameters,Lower,Upper)} & \text{if} b_1 \leq x \leq Upper \\ 1 & \text{if} x > Upper \end{array} \right\}$$

(Notes: pdf_{ccgt_p}(x,parameters,Lower,Upper), cdf_{ccgt_p}(x,parameters,Lower,Upper), $L_{0_{ccgt_p}}$ (parameters,Lower,Upper), $M_{0_{ccgt_p}}$(parameters,Lower,Upper), and $R_{0_{ccgt_p}}$(parameters,Lo -wer,Upper) are shortened as $pdf_{ccgt_p}(x)$, $cdf_{ccgt_p}(x)$, $L_{0_{ccgt_p}}$, $M_{0_{ccgt_p}}$, and $R_{0_{ccgt_p}}$ in the equations of pdf_{ccgt_p} and cdf_{ccgt_p}.)

3.3 GARCH with Student-t, Clustered Censored Student-t in polynomial form and exponential form; and their Empirical Performance

The following models, $GARCHST$, $GARCHCCST$, and $GARCHCCST_p$, have the same conditional variance generating function as

$$h_t = \kappa + \alpha h_{t-1} + \beta u_{t-1}^2$$

The error terms have different distributions.

1. '$GARCHST$'[2]

$$u_t \sim ST(0, h_t, v)$$

2. '$GARCHCCST$'[3]

$$u_t \sim CCST((0; h_t; v; l_1; r_1; m_1; m_2), Lower, Upper)$$

[2]This expression of $u_t \sim ST(\mu, \sigma^2, v)$ means that u_t is a variable that follows a $Student-t$ that has a location parameter as μ, a latent scale parameter as σ, and a degree of freedom as v. This distributional model is in section 3.2.

[3]This expression of $u_t \sim CCST((\mu; \sigma^2; v; l_1; r_1; m_1; m_2), Lower, Upper)$ means that u_t is a variable that follows a clustered censored Student-t (in exponential clustered form) that has the location parameter as μ, the latent scale parameter as σ, the degree of freedom as v, the left and right clustering rates as l_1 and r_1, the left slope as m_1, the right slope as m_2, the lower bound as $Lower$, and the upper bound as $Upper$. This distributional model is in section 3.2.

3. '$GARCHCCST_p$'[4]

$$u_t \sim CCST_p((0;h_t;v;l_1;r_1;\rho_1;\rho_2), Lower, Upper)$$

3.3.1 Data

The data used in this section include ChinaTrust, Clevo, Fubon, GDPower, LVMH, and Posco, in which the $p-values$ of out-of-sample LR_{cc} tests of the fitted $GARCHCCN$ are lower than 10% in Chapter 2. The starting and ending dates are in table H.0.2. Another stock, *Lotes* from December 10, 2007 to May 14, 2014 is also tested. A common way to analyse the time evolution of the returns is sequential differences of the natural logarithm of prices p_t, $u_t = log(p_t/p_{t-1}) \times 100$.

3.3.2 Out-of-sample Tests

The objective of this section is to find the model which gives most precise out-of-sample VaR forecasts among $GARCHST$, $GARCHCCST$, and $GARCHCCST_p$. The model parameters are re-estimated via MLE based on sufficient number of recorded financial returns, from t_1 to $t_1 + T_1 - 1$, at each increment of t_1 from 1, as is common in actual applications. Thus, out-of-sample Kupiec tests, $E(shortfall^2)$, and LR_{cc} are illustrated. T_1 is set as $T - T_0$, in which T is the number of observations in data. The VaRs for the last T_0, which is defined as 400, dates in the data are evaluated to choose the best conditional distribution out of a model group consisting of Student-t, $CCST$, and $CCST_p$.

$GARCHCCST$ and $GARCHCCST_p$ have smaller BIC values than $GARCHST$ except in Posco. The obvious advantage of a polynomial clustered form is that the fitted $GARCHCCST_p$ has much smaller standard deviations for κ, α, β estimates than $GARCHCCST$ has in Clevo, GDPower, and Lotes (table L.0.3).

The out-of-sample VaR measures are shown in table L.0.1. Both Kupiec and LR_{cc} values of $GARCHCCST$ and $GARCHCCST_p$ are lower than those of $GARCHCCN$ in each stock. For example, in Clevo, when p is 0.1, the Kupiec and LR_{cc} tests of the fitted $GARCHCCN$ are 11.9226 and 14.2571, but the tests are 4.4218 and 8.6523 for both $GARCHCCST$ and $GARCHCCST_p$. In Lotes, the $p-value$s change from 0.005 to 0.1 for both the $Kupiec$ LR test, and the LR_{cc} by using $GARCHCCST$ and $GARCHCCST_p$ instead of $GARCHST$. $GARCHCCST$ and $GARCHCCST_p$ increase the $p-value$s of the $Kupiec$ and LR_{cc} tests

[4]This expression of $u_t \sim CCST_p((\mu;\sigma^2;v;l_1;r_1;\rho_1;\rho_2), Lower, Upper)$ means that u_t is a variable that follows a clustered censored $Student-t$ (in polynomial clustered form) that has the location parameter as μ, the latent scale parameter as σ, the degree of freedom as v, the left and right clustering rates as l_1 and r_1, the left degree of polynomial as ρ_1, the right degree of polynomial as ρ_2, the lower bound as $Lower$, and the upper bound as $Upper$. This distributional model is in section 3.2.

from 0.005 to 0.05 and from 0.005 to 0.025 compared to $GARCHST$ model in Clevo. Similarly, in GDPower, $GARCHST$ is not rejected as a good model with a confidence interval of 97.5% but both $GARCHCCST$ and $GARCHCCST_p$ are not rejected with a smaller confidence interval of 95% for both tests. In ChinaTrust and Posco, $p - values$ increase from 0.1 to much greater values. For example, the $Kupiec$ tests of $GARCHCCST$ and $GARCHCCST_p$ in Posco for p of 0.1 are 0.7219 compared with 3.0143 of $GARCHST$.

Overall, the two different forms of clusters have similar $Kupiec$ and $Christoffersen's$ tests and there is no evidence showing which form of clusters performs better according to the $Kupiec$ LR and $Christoffersen's$ tests. Both forms of clusters are useful at improving out-of-sample VaR forecasts for five out of seven stocks in table L.0.1, while in Fubon and LVMH, the three models have almost identical values of tests.

3.3.3 Moment Simulations and Comparisons

If a model is suitable for a data series, the moments of a simulated data with a large data size by using the fitted model should be closer to the true moments than those of other un-suitable models. Xu et al. (2011) made an comparison of empirical moments across their model and other alternative models to suggest that their model provides a closer match for the first four moments. Similarly, the purpose of this section is to compare how close the simulated moments of the fitted models are to the true moments in order to select the best conditional distributional model among a selection group. The simulation data size is 50,000. The moments include mean, variance, skewness, kurtosis, $E(u_t u_{t-1})$, and $E(u_t^2 u_{t-1}^2)$. This moment simulation method finds its preferred model for a series of financial returns when the sum, S, of squared residuals at each moment, is smallest among fitted models. The lowest S is made bold in Table L.0.4. Table L.0.4 shows that $GARCHCCST$ and $GARCHCCST_p$ have much lower S values than the conventional $GARCHST$. The S value of $GARCHST$ is greater or equal to 6.7929 times of that of either $GARCHCCST$ or $GARCHCCST_p$. In Clevo, the S of $GARCHST$ is 5.1437e+005 times of that of $GARCHCCST$.

In particular, among the first four moments, the biases of variance and kurtoses are more noticeable than those of other moments. Variances simulated by $GARCHCCST$ and $GARCHCCST_p$ are much closer to that of corresponding stock than that by $GARCHST$ for all the seven stocks except LVMH. In LVMH, the variances are 4.2086 for $GARCHST$, 3.3803 for $GARCHCCST$, 3.7367 for $GARCHCCST_p$, and 4.0454 for the data. The simulated variances of the three time series models have very similar biases (differences between the simulated moments and empirical moments) in LVMH, while in other stocks, e.g., Clevo and GDPower, simulated variance of $GARCHST$ is at least double of that of $GARCHCCST$, $GARCHCCST_p$, or the data. At the same time, kurtoses simulated by $GARCHCCST$ and $GARCHCCST_p$ have lower biases than that by $GARCHST$ in each stock. For instance, in ChinaTrust with an empirical kurtosis equal to 5.1582, the kurtoses of $GARCHCCST$ and $GARCHCCST_p$ are 4.5925 and 5.0888, while the simulated kurtosis of $GARCHST$ is 74.0920.

The large differences between the kurtoses of empirical data and simulated data of fitted $GARCHST$ models are consistent with the findings in Heracleous (2007) that $GARCHST$ model and sample kurtosis give biased and inconsistent estimates for the degree of freedom parameter. The reason for the large biases is that simulate data generated by using Student-t distribution or $GARCHST$ usually contain some extremely large outliers. In table 3.3.1, "sample moments" are the moments simulated by using fitted models; "empirical moments" are moments derived from data series. Microsoft data used here is the same as in Chapter 2. It is found that if there is no bounds, the minimum and maximum of "sample moments" are much larger than empirical ones by using $GARCHST$. A large outlier can deviate sample variance and kurtosis away from empirical moments dramatically (in table L.0.4). Several of them result in even greater biases. By excluding those outliers, we can have a much better sample variance and kurtosis. "sample moments (excluding simulated variables out of [-35.8315, 17.8692])" in table 3.3.1 are obtained accordingly. However, by doing this, we manually add a set of bounds on the simulation. On the other hand, a handful of outliers have a small (sometimes negligible) impact on *cdf* and VaR. As a result, the disadvantages of $GARCHST$ compared to other two models in out-of-sample VaR estimates (table L.0.1) are not as apparent as those in sample moments. When price limits exist, $GARCHCCST_p$ and $GARCHCCST$ do not seem to have large biases in moment simulations not only because of bounds but also for clusters retained. As shown in table 3.3.1, sample moments by deleting simulated variables out of the domain of empirical data still exhibit comparably larger biases than the sample moments derived by using fitted $GARCHCCST$ and $GARCHCCST_p$ in table L.0.4.

In addition, $GARCHCCST_p$ has lower S's in two out of seven stocks, while the S values of $GARCHCCST$ are 24.4734 compared to 310.1954 of $GARCHCCST_p$ in ChinaTrust, 502.6951 to $1.0799e+003$ in Clevo, 5.3881 to 25.6727 in Fubon, 318.3817 to $1.2635e+003$ in Lotes, and 943.5703 to $1.0498e+003$ in Posco. Therefore, $GARCHCCST$ is preferred to $GARCHCCST_p$ via the S selection rule.

3.4 Conclusions

In Chapter 2, $GARCHCCN$ is demonstrate to be more suitable than censored, truncated, and unlimited $GARCH$ model under Gaussian for its greater $p-values$ of in-sample Kupiec tests and lower out-of-sample LR_{cc} in most stocks. Similarly, $GARCHCCST$ and $GARCHCCST_p$ outperform $GARCHST$ according to the $p-values$ of out-of-sample VaR measures and S values in moment simulations. In a word, clustered censored prop-

Table 3.3.1: Microsoft: Comparisons between sample moments (sample size of 50,000) and empirical moments

κ	α	β	v	$-LOGL$	BIC		
0.0185***	0.9390***	0.0604***	5.3063***	1.5186e+004	3.0408e+004		
(0.0055)	(0.0069)	(0.0073)	(0.3084)				
Empirical moments							
minimum	maximum	mean	variance	skewness	kurtosis	$E(u_t u_{t-1})$	$E(u_t^2 u_{t-1}^2)$
-35.8315	17.8692	0.0869	4.9401	-0.6136	17.9271	0.0446	68.8428
Sample moments							
minimum	maximum	mean	variance	skewness	kurtosis	$E(u_t u_{t-1})$	$E(u_t^2 u_{t-1}^2)$
-171.2947	157.7349	-0.0267	21.9183	-0.0355	306.6418	-0.0154	3.2751e+004
Sample moments (excluding simulate variables out of [-35.8315, 17.8692])							
minimum	maximum	mean	variance	skewness	kurtosis	$E(u_t u_{t-1})$	$E(u_t^2 u_{t-1}^2)$
-35.7627	17.8665	-0.0387	7.8015	-1.2123	20.5928	0.0297	322.2157

Notes: $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$

erty is needed for improving risk forecasts.

However, many other questions we have under a bounded environment remain unanswered. For instance, are there spillover effects from previous periods' leftover to this period's return or volatility? Would spillover effects change with respect to bounds? To answer these questions, the first step we take is to define an appropriate mapping from an underlying distribution to the related observable distribution. The ideal mapping rule is one-to-one, but we find that in an one-to-one mapping, an underlying return within the bounds may need to be mapped into an observed value different from its original value. This fact is not consistent with the traditional mapping rule, in which returns within bounds stay the same after being mapped (Wei (2002)). The next section describes some approaches we used in detecting spillover effects.

3.5 Future Research Interest: Spillovers

As a policy maker, it is interesting to find how a set of bounds influence trading activities. Through changes of bounds and trading limit policies, a policy maker may infer a relationship between trading activities and bounds. It is possible to find how spillovers, differences between latent stock returns and their realized stock returns, from past periods influence trading prices today. Spillovers are normally referred to correlations among different financial returns but in this thesis, spillovers are unrealized parts of trading prices. Latent stock returns are not observed in reality and this makes an analysis of spillovers extremely difficult. We believe that it is possible to test spillover effects by using a time series model. An appropriate mapping rule is fundamental for the success of this model.

3.5.1 Simulation of GARCH(1,1) with spillovers

In this section, we examine the estimate biases due to spillovers in RGP, an abbreviation that stands for return generating process. The mapping rule used is a group mapping since a value outside of bounds are mapped to any variable in a range within the bounds.

The leftovers from the unrealized returns over past days may have effects on today's observed return. The simulations in Wei (2002) added the sum of the differences between all past days' observed returns and underlying returns to today's return. The author assumed no effect from the leftovers to the underlying volatility. The dynamic is explained as follows. The underlying return at time t is denoted as u_{true_t}, the observed return is u_{seen_t}, and the sum of the accumulated leftovers from the first period until time t and the underlying return of u_{true_t} is u_{middle_t}.

Given a series of returns, $\{u_{true_t}\}_{t=1}^{T}$, generated from a $GARCH(1,1)$ process with $\kappa = 0.1$, $\alpha = 0.8$, and $\beta = 0.1$, the existence of two bounds causes the spillover effects. At the first time period, there is no spillover. Therefore, $u_{middle_1} = u_{true_1}$.

The mapping rule is defined as follows. The underlying conditional variance generation process is not influenced by bounds.

$$h_t = \kappa + \alpha h_{t-1} + \beta u_{true_{t-1}}^2$$

The underlying mean at each time t is 0. u_{middle_t} is mapped into u_{seen_t}. We also assume the mapped values of u_{middle_t} will make the distribution of u_{seen_t} to be a CCN distribution with parameters of $(0; h(t); l_{1_t}; r_{1_t}; m_1; m_2)$ at each time period of t. Let $u_{seen_t} = u_{middle_t}$ if $u_{middle_t} \in [Lower, Upper]$. To simplify the process, we let $m_1 = -m_2$ and we can change the value of m_2 in simulations. The clustering rates of l_{1_t} and r_{1_t} change with respect to the clustering coefficients. To make $\Omega_{ccn} = 1$ at each time t, l_{1_t} and r_{1_t} have to satisfy the following equations:

1. $cdf_{ccn}(l_{1_t}{*}Lower, (0; h(t); l_{1_t}; r_{1_t}; -m_2; m_2), Lower, Upper) = F\left(l_{1_t} * Lower, 0, \sqrt{h(t)}\right)$

2. $cdf_{ccn}(r_{1_t}{*}Upper, (0; h(t); l_{1_t}; r_{1_t}; -m_2; m_2), Lower, Upper) = F\left(r_{1_t} * Upper, 0, \sqrt{h(t)}\right)$

Hence, l_{1_t} and r_{1_t} are derived from the values of m_2, $h(t)$, $Lower$, and $Upper$.

Let $pa_t = (0; h(t); l_{1_t}; r_{1_t}; -m_2; m_2)$. If $u_{middle_t} < Lower$, $u_{seen_t} \in [Lower, l_{1_t} * Lower]$

and the *pdf* for u_{seen_t} (the distribution of the mapped value) is

$$\frac{pdf_{ccn}(u_{seen_t}, pa_t, Lower, Upper) - f\left(u_{seen_t}, 0, \sqrt{h(t)}\right)}{cdf_{ccn}(l_{1_t} * Lower, pa_t, Lower, Upper) - F\left(l_{1_t} * Lower, 0, \sqrt{h(t)}\right) + F\left(Lower, 0, \sqrt{h(t)}\right)} \tag{3.5.1}$$

If $u_{middle_1} > Upper$, $u_{seen_t} \in [r_{1_t} * Upper, Upper]$ and the pdf for u_{seen_t} is

$$\frac{pdf_{ccn}\left(u_{seen_t}, pa_t, Lower, Upper\right) - f\left(u_{seen_t}, 0, \sqrt{h(t)}\right)}{1 - cdf_{ccn}(r_{1_t} * Upper, pa_t, Lower, Upper) + F\left(r_{1_t} * Upper, 0, \sqrt{h(t)}\right) - F\left(Upper, 0, \sqrt{h(t)}\right)} \tag{3.5.2}$$

u_{seen_1} is the mapped value of u_{middle_t} according to this mapping rule. The leftover is $u_{middle_1} - u_{seen_1}$ for the second time period. Let λ be the discount factor. $u_{middle_2} = u_{true_2} + \lambda * (u_{middle_1} - u_{seen_1})$. u_{seen_2} is the mapped value of u_{middle_2}, and so on. In the simulations, we change λ and m_2 to show how the parameter estimates change accordingly. λ is either 0.8 or 1. λ is not greater than 1 because a discount factor greater than 1 will result in diffusion of returns. m_2 is either 1 or 2. The bounds are $[-3, 3]$. An simulation with a data size of 5000 is done according to the mapping rule mentioned above.

In table L.0.2, when $\lambda = 1$ and m_2 increases from 1 to 2, the downward biases of κ's by $GARCHCCN$ and $GARCH$ increase. In $GARCHCCN$, κ changes notably from 0.0824 to 0.0694 and the true value is 0.1. The downward biases of β's decrease. As an illustration, β increases from 0.0852 to 0.0997 and the true value is 0.1. However, when $\lambda = 0.8$, as m_2 increases, the downward biases of κ's by $GARCHCCN$ and $GARCH$ decrease, e.g., from 0.0857 to 0.0902 in $GARCHCCN$. The downward biases of β's change to upward biases, e.g., from 0.0893 to 0.1158 in $GARCHCCN$. If $m_2 = 2$ or $m_2 = 1$, as λ increases, the downward biases of κ's increase. When $\lambda = 1$, as m_2 rises, the upward biases of α's for both fitted models increase, while when $\lambda = 0.8$, the upward biases of α change to downward biases. This means lower value of λ and higher value of m_2 have contrary effects to κ and α estimates but affect β estimates in the same direction. In addition, a greater true value of m_2 leads to a larger right clustering coefficient. Correspondingly, clusters are steeper.

It is hard to describe how a lower λ affects the clustering coefficient estimates because both the clustering rates and clustering shapes change. When $m_2 = 1$, a lower λ is accompanied by steeper clusters. When $m_2 = 2$, a smaller λ results in flatter left clusters and steeper right clusters. Since l_1 and r_1 are related to the clustering coefficients, as clusters become more obvious, the clustering rates have to become greater so the clustering ranges become smaller. This sequential changes are needed to make $\Omega_{ccn} = 1$ at each time t. The estimated clustering rates and coefficients coincide with this fact.

Due to the time varying conditional variance, the clustering rates of l_1 and r_1 change over time. However, we can still obtain the values of l_{1_t} and r_{1_t} each period from the simulation process. The mean, median, standard deviation of these two variables, each denoted as $mean(l_1)$, $median(l_1)$, $std(l_1)$, $mean(r_1)$, $median(r_1)$, and $std(r_1)$ in table L.0.2, are presented. There are upward biases about 0.07 in the estimates of either l_1 and r_1 by using $GARCHCCN$ model if $mean(l_1)$ and $mean(r_1)$ are used as the estimates of l_1 and r_1.

Overall, the fitted $GARCHCCN$ models have lower BIC values than $GARCH$. The models capture the clusters in the simulations although the clustering coefficients have much greater magnitudes than the true values of m_1 and m_2. For instance, in the first simulation, left clustering coefficient is -27.0139 while the true value is -1. The right clustering coefficient is 30.7408 while the true value is 1. Although the large biases of these clustering coefficients might be due to the wrong assumption of fixed clustering rates (while in fact they are changing on each date t), the biases of parameter estimates demonstrate that it is necessary to examine the spillover effects when doing a financial modelling. Moreover, the accumulations of leftovers may have impact on the underlying variance as well as the mean. More research need to be done on spillover effects.

3.5.2 Mapping Rules

As discussed in Chapter 1, the relationship between daily limits and the underlying/population standard deviation was investigated in past literature especially for arguing the pros and cons of price limits. Research for this purpose compare data with and without price limits and some comparisons are completed by using data with different limits. It is not difficult to find countries where price limits got aborted after a period of imposition. It is also possible to find stock returns with different limits over time (Maghyereh et al (2007) and Kim (2001)). However, the comparison of stock returns in different time horizons may not be convincing due to economic cycles or other interior and exterior factors that might alter trading prices.

Thus, a stock that is traded in two markets (one with and the other without price limits) simultaneously can be used. Nevertheless, stock returns are not independent from education and income levels of traders. It is unlikely that the same stock traded in two different countries have equal volatility given different wealth (Li (2007)) and preferences. It has been shown that noisy traders have impact on stock performance. Rational arbitrageurs with limited horizon do not eliminate the belief that the price fluctuates randomly in near future (Brown (1999) and Bhushan et al.(1997)). Chang et al. (2009) target at the fact that un-informed traders exacerbate the magnet effect. Cho et al. (2003) find the acceleration trends to both lower and upper bounds. Returns within the 3% of the lower and upper bounds affect both conditional mean equation of the return and conditional variance equation for next period of time. However, it is hard to separate price momentum effects (Jegadeesh and Titman (1993)), a clustering of price increase or decrease, from spillover and magnet effects. Furthermore, Lee and Swaminathan (2000) find that price momentum effects reverse over over Years 3 through 5 but not through the third year following portfolio formation. Kim and et al (2008) compare the effects from trading halts with those from price limits to stocks in the Spanish Stock Exchange in the period of frequent enforcements of trading halts and price limit hits. Others compared variances right after the returns hitting the limits with those following the returns within the bounds (Kim and Rhee (1997)), but rough comparisons can not explain spillover effects if more details are wanted, e.g., change of underlying mean/variance with respect to the changes of bounds. An adequate mapping rule needs to be analysed in order to find meticulous details of spillover effects.

In this section, I suggest using a mixture of one-to-one and group mappings between a normal distribution and a CCN, because in a CN distribution (a special case of CCN) a range of variables, $x < Lower$ ($Lower$ is the lower bound, $Upper$ is the upper bound), are mapped into $Lower$. However, the empirical evidence in Chapter 1, 2, and Section 3.3 show that clusters might not be right at bounds. Masters and Gurley (2003) proposed a stochastic non-Gaussian simulation method capable of reliably preserving both spectral and probabilistic contents for a distribution deviating from Gaussian due to extreme environmental pressure, such as strong winds (Gioffre et al. (2000), Kumar and Stathopoulos (2000)). I can use this method since a CCN is a distortion of a Gaussian distribution. The percentiles of a CCN do not change from the underlying normal distribution. A variable x of a normal distribution can be matched with a y with the corresponding CCN by using $cdf_{ccn}(y, pa, Lower, Upper) = F\left(x, pa(1), \sqrt{pa(2)}\right)$, given $pa = (\mu; \sigma^2; l_1; r_1; m_1; m_2)$. The underlying normal distribution is $N(pa(1), pa(2))$. Thus, cumulative density function mapping (cdf mapping) can be combined with this so called group mapping.

It is easy to find a real life example that is related to this mapping rule. When a class has extremely high or low grades, the distribution of grades is unlikely to be a Gaussian distribution. An instructor adds more to poor grades in order to force the distribution of the grades closer to a normal distribution. This mapping rule from a non-Gaussian to a Gaussian is one to one and the sequence from highest to the lowest marks is not changed. The ranks of students are kept the same before and after mapping. In a word, the cdf is not changed.

Figures N.1, N.2, and N.3 demonstrate the mapping rule from a random variable of x with a normal distribution to y, a variable with a CCN distribution. The intersections of the purple lines with the two $cdf's$ in these figure give an example of mapping between y and x. The intersection of the purple line with the red curve is y and that of the purple line with the green curve is x. There is a unique intersection between the red and green curves in each of figures N.1 and N.2. Let this intersection be point A, the intersection between the blue line and the two *cdf* curves. Let x^* be the mapped value of point A to the horizontal axis.

$$\Theta \in [0,1]$$

$$E(x-y) = \int_0^1 (F^{-1}(\Theta,\mu,\sigma) - cdf_{ccn}^{-1}(\Theta, pa, Lower, Upper))\, \mathrm{d}\Theta$$

F^{-1} is the inverse cumulative function of normal and cdf_{ccn}^{-1} is the inverse cumulative function of CCN. When $\Theta = 0$ or $\Theta = 1$, $F^{-1}(\Theta,\mu,\sigma)$ is not a number in MATLAB. Therefore, we set $\Theta_1 = 10^{-6}$ (this is just an example since what value Θ_1 is depends on the *pdf* of CCN). If $\Theta \in [0+\Theta_1, 1-\Theta_1]$, the *cdf* mapping is used. For $\Theta < \Theta_1$, we set a mapping from CCN variables in the domain of $[Lower, cdf_{ccn}^{-1}(\Theta_1, pa, Lower, Upper)]$ to normal variable in the domain of $(-\infty, F^{-1}(\Theta_1,\mu,\sigma)]$ and vice versa. Similarly, we have a group mapping from CCN variables in the domain of $[cdf_{ccn}^{-1}(1-\Theta_1, pa, Lower, Upper), Upper]$ to normal variable in the domain of $[F^{-1}(1-\Theta_1,\mu,\sigma),\infty)$.

$$E(x-y) = \int_{-\infty}^{\infty} (cdf_{ccn}(x, pa, Lower, Upper) - F(x,\mu,\sigma)) * x\, \mathrm{d}x = \mu - mean_{ccn}(pa, Lower, Upper)$$

The value can be found by using simulations. On the contrary, $E(x-y)^2 = \int_0^1 (F^{-1}(\Theta,\mu,\sigma) - cdf_{ccn}^{-1}(\Theta, pa, Lower, Upper))^2\, \mathrm{d}\Theta$ is not easy to derived. It is easier to calculate the first and second moments of leftovers, $E(x-y)$ and $E(x-y)^2$ in group mapping, e.g. the mapping rule in 3.4.1., but the leftover of group mapping is the mean of one-to-one mapping over a domain and so spillover effects computed in a group mapping are not precise.

The one-to-one mapping has its own problem as well. It is hard to explain why an underlying variable inside of the bounds is mapped to a different value with a CCN distribution. We believe that some trading offers inside of the bounds are crowded out by the offers made by people whose ideal prices are outside of the bounds. However, it may not be reasonable that crowding out effects result in a mapping rule following the *cdf* mapping rule perfectly.

Nevertheless, one-to-one mapping is much simpler than group mapping since under the assumption that CCN is not symmetric, matching up the domains of mapping can be complicated. As a result, we try the one-to-one mapping rule. Let underlying parameters of a CCN be $(0; 2.7^2; 0.8; 0.7; 0.99; -0.99)$ and bounds be $[-5, 5]$, by using a mapping simulation of data size 1000, latent values are plotted along with observed values in figure N.4. In figure N.5, underlying parameters of a CCN are $(0; 2.7^2; 0.8; 0.7; 0.99; -0.99)$ and bounds are $[-7.5, 7]$. Latent and observed values diverge around bounds. In these two figures, the latent values are greater than their related observed values. The graphs of the *cdf* mapping for bounds of $[-5, 5]$ and $[-7.5, 7]$ are shown as figures N.6 and N.7. In figure N.8, bounds are $[-14, 14]$. An underlying variable can be mapped into a value that is greater than, equal to, or less than its latent value.

CCN and $GARCHCCN$ are used in the following set-up containing spillover effects. $Chilisin$ (from September 27, 2001 to April 24, 2015), a Taiwanese stock, is used as an example. The mapping rule, a combination of group and one-to-one mapping, explained right above is used. Let $\Theta = cdf_{ccn}(y, pa, Lower, Upper)$.

$$x = F^{-1}(\Theta, pa(1), pa(2))$$

This whole mapping from y to x is denoted as $x = mappingback(y, pa, Lower, Upper)$. The first moment difference is $x - y$ and the second moment difference is $(x - y)^2$. t stands for the date. Suppose the return series of $u_{t=1}^{T}$ have spillover effects from both the first and second moments based on a $GARCHCCN$ model. The parameters include κ, α, β, l_1, r_1, m_1, m_2, CL_1 (the spillover coefficient for the first moment when the true value is lower than the lower bound), CR_1 (the spillover coefficient for the first moment when the true value is greater than the upper bound), CL_2 (the spillover coefficient for the second moment when the true value is lower than the lower bound), and CR_2 (the spillover coefficient for the second moment when the true value is greater than the upper bound). For any period of t, $pa_t = (mean_t; h_t; l_1; r_1; m_1; m_2)$.

$$u_{middel_t} = mappingback(u_t, pa_t, Lower, Upper)$$

$$c_{1_t} = 0$$

$$c_{2_t} = 0$$

If $u_{middel_t} < Lower$, $c_{1_t} = CL_1$ and $c_{2_t} = CL_2$; if $u_{middel_t} > Upper$, $c_{1_t} = CR_1$ and $c_{2_t} = CR_2$.

$$mean_{t+1} = c_{1_t} * (u_{middel_t} - u_t)$$

$$h_{t+1} = \kappa + \alpha h_t + \beta(u_t - mean_t)^2 + c_{2_t} * (u_{middel_t} - u_t)^2$$

This model is denoted as $GARCHCCN_{mapping}$.

3.5.3 Conclusions

In table 3.5.1, the fitted $GARCHCCN$ models with or without the spillovers have almost identical $LOGL$ and $GARCHCCN_{mapping}$ may have a greater BIC value than $GARCHCCN$ (table 3.5.1). One of the reasons is that by using $GARCHCCN$ relative bounds are large. For instance, table I.0.1 shows the bounds are wider than three times and some are over 10 times of the underlying standard deviation. There are very few variables causing spillovers. According to table E.0.2, it is strongly supported that $GARCHCCN$ has a greater BIC than $GARCHST$. The underlying distribution assumed might be wrong at the first place and the mapping rule needs to be adjusted as well. The differences of

v values between the fitted $GARCHCCST$ and $GARCHCCST_p$ and those of the fitted $GARCHST$ in table L.0.3 suggest that there might be more variables causing spillovers if the underlying conditional distributional model is Student-t rather than normal. Moreover, figure 1.4 and table 1.4.1 suggest that $GARCH$ with clustered censored Laplace and spillover effects is worth doing.

Table 3.5.1: Fitted $GARCHCCN_{mapping}$ and $GARCHCCN$ Models

Chilisin parameters	$GARCHCCN_{mapping}$	$GARCHCCN$
κ	0.2895***	0.2793***
	(0.0098e-03)	(0.0648)
α	0.8733***	0.8728***
	(0.0422e-03)	(0.0232)
β	0.0385***	0.0430***
	(0.0024e-03)	(0.0075)
l_1	0.7342***	0.7330***
	(0.0305e-03)	(0.0136)
r_1	0.8629***	0.8632***
	(0.0897e-03)	(0.0085)
m_1	−0.7044***	−0.7147***
	(0.0080e-03)	(0.1389)
m_2	3.8326***	3.9304***
	(0.1695e-03)	(0.3879)
CL_1	−0.0370***	
	(0.0011e-03)	
CR_1	−0.1047***	
	(0.6666e-03)	
CL_2	0.0537***	
	(0.0025e-03)	
CR_2	0.0655***	
	(0.0017e-03)	
$-LOGL$	7.3317e+03	7.3348e+03
BIC	1.4753e+004	**1.4726e+004**

Notes: $^*p < .05$, $^{**}p < .01$, $^{***}p < .001$

APPENDICES

Appendix A

The First Four Moments of CN and TN

A.0.4 The first four moments of standard normal with two bounds

$x \sim N(\mu; \sigma^2)$ and if $x \in [Lower, Upper]$

$$y = \frac{x - \mu}{\sigma}$$

Let $Lower_1 = \frac{Lower - \mu}{\sigma}$ and $Upper_1 = \frac{Upper - \mu}{\sigma}$. Therefore, $y \in [Lower1, Upper1]$. Consequently,

$$f(x; \mu, \sigma) = \frac{f(y; 0, 1)}{\sigma}$$

$$F(x; \mu, \sigma) = F(y; 0, 1)$$

y is a variable with standard normal distribution.

$$\forall i \in \{1, 2, 3, 4\}$$

$$stdint_i(Lower_1, Upper_1) = \int_{Lower_1}^{Upper_1} y^i f(y; 0, 1)\, \mathrm{d}y$$

If $i = 1$, it is equal to $-f(Upper_1; 0, 1) + f(Lower_1; 0, 1)$. If $i = 2$, it is equal to $-Upper_1 f(Upper_1; 0, 1) + Lower_1 f(Lower_1; 0, 1) + F(Upper_1; 0, 1) - F(Lower_1; 0, 1)$. If $i = 3$, it is equal to $-{Upper_1}^2 f(Upper_1; 0, 1) + {Lower_1}^2 f(Lower_1; 0, 1) + 2stdint_1(Lower_1, Upper_1)$. If $i = 4$, it is equal to $-{Upper_1}^3 f(Upper_1; 0, 1) + {Lower_1}^3 f(Lower_1; 0, 1) + 3stdint_2(Lower_1, Upper_1)$.

$$normint_i(\mu, \sigma, Lower, Upper) = \int_{Lower}^{Upper} x^i * f(x, \mu, \sigma)\, \mathrm{d}x$$

If $i = 1$, it is equal to $\mu * (F(Upper, \mu, \sigma) - F(Lower, \mu, \sigma)) + \sigma * stdint_1(Lower_1, Upper_1)$.

If $i = 2$, it is equal to $\sigma^2 * stdint_2(Lower_1, Upper_1) + 2\mu\sigma * stdint_1(Lower_1, Upper_1) + \mu^2 * (F(Upper, \mu, \sigma) - F(Lower, \mu, \sigma))$.
If $i = 3$, it is equal to $\sigma^3 * stdint_3(Lower_1, Upper_1) + 3\mu^2\sigma * stdint_1(Lower_1, Upper_1) + 3\sigma^2\mu * stdint_2(Lower_1, Upper_1) + \mu^3(F(Upper, \mu, \sigma) - F(Lower, \mu, \sigma))$.
If $i = 4$, it is equal to $\sigma^4 * stdint_4(Lower_1, Upper_1) + 4\mu^3\sigma * stdint_1(Lower_1, Upper_1) + 6\sigma^2\mu^2 * stdint_2(Lower_1, Upper_1) + 4\sigma^3\mu * stdint_3(Lower_1, Upper_1) + \mu^4 * (F(Upper, \mu, \sigma) - F(Lower, \mu, \sigma))$.

A.0.5 The First Four Moments of TN

$$mean_{tn}((\mu;\sigma^2), Lower, Upper) = \frac{normint_1(\mu, \sigma, Lower, Upper)}{F(Upper, \mu, \sigma) - F(Lower, \mu, \sigma)} \tag{A.0.1}$$

$$var_{tn}((\mu;\sigma^2), Lower, Upper) = \frac{normint_2(\mu, \sigma, Lower, Upper)}{F(Upper, \mu, \sigma) - F(Lower, \mu, \sigma)} - (mean_{tn}((\mu;\sigma^2), Lower, Upper))^2 \tag{A.0.2}$$

$$\begin{aligned} &skewness_{tn}((\mu;\sigma^2), Lower, Upper) \\ &= [\frac{normint_3(\mu, \sigma, Lower, Upper)}{F(Upper, \mu, \sigma) - F(Lower, \mu, \sigma)} \\ &\quad - 3mean_{tn}((\mu;\sigma^2), Lower, Upper)\frac{normint_2(\mu, \sigma, Lower, Upper)}{F(Upper, \mu, \sigma) - F(Lower, \mu, \sigma)} \\ &\quad + 2mean_{tn}((\mu;\sigma^2), Lower, Upper)^3]/[var_{tn}((\mu;\sigma^2), Lower, Upper)^{3/2}] \end{aligned} \tag{A.0.3}$$

$$\begin{aligned} &kurtosis_{tn}((\mu;\sigma^2), Lower, Upper) \\ &= [\frac{normint_4(\mu, \sigma, Lower, Upper)}{F(Upper, \mu, \sigma) - F(Lower, \mu, \sigma)} - 3mean_{tn}((\mu;\sigma^2), Lower, Upper)^4 \\ &\quad + \frac{6mean_{tn}((\mu;\sigma^2), Lower, Upper)^2 normint_2(\mu, \sigma, Lower, Upper)}{F(Upper, \mu, \sigma) - F(Lower, \mu, \sigma)} \\ &\quad - \frac{4mean_{tn}((\mu;\sigma^2), Lower, Upper) normint_3(\mu, \sigma, Lower, Upper)}{F(Upper, \mu, \sigma) - F(Lower, \mu, \sigma)}]/[var_{tn}((\mu;\sigma^2), Lower, Upper)^2] \end{aligned} \tag{A.0.4}$$

A.0.6 The First Four Moments of CN

If $i \in 1, 2, 3, 4$,

$$cnint_i((\mu;\sigma^2), Lower, Upper) = \int_{Lower}^{Upper} pdf_{cn}(x) x^i \, \mathrm{d}x \tag{A.0.5}$$

Therefore, $\forall i = 1, 2, 3, 4$,

$$\begin{aligned} cnint_i((\mu;\sigma^2), Lower, Upper) &= normint_i(\mu, \sigma, Lower, Upper) \\ &\quad + (F(Lower, \mu, \sigma))Lower^i + (1 - F(Upper, \mu, \sigma))Upper^i \end{aligned} \tag{A.0.6}$$

$$mean_{cn}((\mu;\sigma^2), Lower, Upper) = cnint_1((\mu;\sigma^2), Lower, Upper) \tag{A.0.7}$$

$$var_{cn}((\mu;\sigma^2), Lower, Upper) = cnint_2((\mu;\sigma^2), Lower, Upper) - mean_{cn}((\mu;\sigma^2), Lower, Upper)^2 \tag{A.0.8}$$

$$\begin{aligned} &skewness_{cn}((\mu;\sigma^2), Lower, Upper) \\ &= [cnint_3((\mu;\sigma^2), Lower, Upper) \\ &\qquad - 3mean_{cn}((\mu;\sigma^2), Lower, Upper)cnint_2((\mu;\sigma^2), Lower, Upper) \\ &\qquad + 2mean_{cn}((\mu;\sigma^2), Lower, Upper)^3]/[var_{cn}((\mu;\sigma^2), Lower, Upper)^{3/2}] \end{aligned} \tag{A.0.9}$$

$$\begin{aligned} &kurtosis_{cn}((\mu;\sigma^2), Lower, Upper) \\ &= [cnint_4((\mu;\sigma^2), Lower, Upper) - 3mean_{cn}((\mu;\sigma^2), Lower, Upper)^4 \\ &\qquad + 6mean_{cn}((\mu;\sigma^2), Lower, Upper)^2 cnint_2((\mu;\sigma^2), Lower, Upper) \\ &\quad -4mean_{cn}((\mu;\sigma^2), Lower, Upper)cnint_3((\mu;\sigma^2), Lower, Upper)]/[var_{cn}((\mu;\sigma^2), Lower, Upper)^2] \end{aligned} \tag{A.0.10}$$

Appendix B

The First Four Moments of CCN

Let x be a variable with a CCN distribution. $pdf_{ccn}(x,(\mu;\sigma^2;l_1;r_1;m_1;m_2),Lower,Upper)$ is the pdf as defined in the CCN section.

Let $y \in [Lower, a_1]$, so

$$\forall i \in \{0,1,2,3,4\}$$

If $m_1 \neq 0$:

$$\begin{aligned} L_i(y,(\mu;\sigma^2;m_1;m_2;l_1;r_1),Lower,Upper) &= \Omega * \int_{Lower}^{y} y^i pdf_{ccn}(x,(\mu;\sigma^2;l_1;r_1;m_1;m_2),Lower,Upper)\,\mathrm{d}x \\ &= \frac{A}{m_1}[y^i * exp(m_1(y-a_1)) - Lower^i * exp(m_1(Lower-a_1))] - \\ & i * L_{i-1}(y,(\mu;\sigma^2;m_1;m_2;l_1;r_1),Lower,Upper) \end{aligned} \tag{B.0.1}$$

$$L_0(y,(\mu;\sigma^2;m_1;m_2;l_1;r_1),Lower,Upper) = \frac{A}{m_1}[exp(m_1(y-a_1)) - exp(m_1(Lower-a_1))] \tag{B.0.2}$$

Let $y = a_1$ in equation B.0.2,

$$L_0 = \frac{A}{m_1}[1 - exp(m_1(Lower-a_1))] \tag{B.0.3}$$

$$L_i = L_i(a_1,(\mu;\sigma^2;m_1;m_2;l_1;r_1),Lower,Upper) \tag{B.0.4}$$

But if $m_1 = 0$:

$$L_i(y,(\mu;\sigma^2;m_1;m_2;l_1;r_1),Lower,Upper) = A\frac{y^{i+1} - Lower^{i+1}}{i+1} \tag{B.0.5}$$

$$L_i = L_i(a_1,(\mu;\sigma^2;m_1;m_2;l_1;r_1),Lower,Upper) = A\frac{a_1^{i+1} - Lower^{i+1}}{i+1} \tag{B.0.6}$$

Let $y \in [a_1, b_1]$, so

$$\forall i \in 1,2,3,4$$

$$\begin{aligned} M_i(y,(\mu;\sigma^2;m_1;m_2;l_1;r_1),Lower,Upper) &= \Omega * \int_{a_1}^{y} y^i pdf_{ccn}(x,(\mu;\sigma^2;l_1;r_1;m_1;m_2),Lower,Upper)\,\mathrm{d}x \\ &= normint_i(\mu,\sigma,a_1,y) \end{aligned} \tag{B.0.7}$$

If y is equal to b_1 in equation B.0.7, the following formula is derived.

$$\begin{aligned} M_i &= \Omega * \int_{a_1}^{b_1} y^i pdf_{ccn}(x,(\mu;\sigma^2;l_1;r_1;m_1;m_2),Lower,Upper)\,\mathrm{d}x \\ &= normint_i(\mu,\sigma,a_1,b_1) \end{aligned} \tag{B.0.8}$$

Let $y \in [b_1, Upper]$, so

$$\forall i \in 1,2,3,4$$

If $m_2 \neq 0$:

$$\begin{aligned} R_i(y,[\mu;\sigma^2;m_1;m_2;l_1;r_1),Lower,Upper) &= \Omega * \int_{b_1}^{y} y^i pdf_{ccn}(x,(\mu;\sigma^2;l_1;r_1;m_1;m_2),Lower,Upper)\,\mathrm{d}x \\ &= \frac{B}{m_2}[y^i * exp(m_2(y-b_1)) - b_1^i] \\ &- i * R_{i-1}(y,(\mu;\sigma^2;m_1;m_2;l_1;r_1),Lower,Upper) \end{aligned} \tag{B.0.9}$$

$$R_0(y,(\mu;\sigma^2;m_1;m_2;l_1;r_1),Lower,Upper) = \frac{B}{m_2}[exp(m_2(y-b_1)) - 1] \tag{B.0.10}$$

Let $y = Upper$ in equation B.0.10,

$$R_0 = \frac{B}{m_2}[exp(m_2(Upper-b_1)) - 1] \tag{B.0.11}$$

For $i = 1,2,3,4$,

$$\begin{aligned} R_i &= \Omega * \int_{b_1}^{Upper} y^i pdf_{ccn}(x,(\mu;\sigma^2;l_1;r_1;m_1;m_2),Lower,Upper) \\ &= \frac{B}{m_2}[y^i * exp(m_2(Upper-b_1)) - b_1^i] - i * R_{i-1} \end{aligned} \tag{B.0.12}$$

If $m_2 = 0$:

$$R_0(y,(\mu;\sigma^2;m_1;m_2;l_1;r_1),Lower,Upper) = B\frac{y^{i+1} - b_1^{i+1}}{i+1} \tag{B.0.13}$$

$$R_0 = R_0(Upper, (\mu; \sigma^2; m_1; m_2; l_1; r_1), Lower, Upper) = B\frac{Upper^{i+1} - b_1^{i+1}}{i+1} \tag{B.0.14}$$

Appendix C

Results from Monte Carlo Simulations for TN, CN, CCN models with a data size of 500 or 5000

Table C.0.1: Simulation List

Experiment No.	True Model	Purpose	Data Size	Table	Rows
1	TN	Bounds change	5000	C.0.2	All
2	TN	Bounds change	500	C.0.3	All
3	CN	Bounds change	5000	C.0.4	All
4	CN	Bounds change	500	C.0.5	All
5	CCN	Bounds change	5000	C.0.6	All
6	CCN	m_1 and m_2 change	5000	C.0.7	All
7	CCN	l_1 and r_1 change	5000	C.0.8	All
8	CCN	Bounds change	500	D.0.2	All
9	CCN	m_1 and m_2 change	500	D.0.3	All
10	CCN	l_1 and r_1 change	500	D.0.4	All
11	TN	Bounds change when μ=0.1	5000	D.0.1	1-3
11	CN	Bounds change when μ=0.1	5000	D.0.1	4-6
11	CCN	Bounds change when μ=0.1	5000	D.0.1	9&10
11	CCN	m_1 and m_2 change when μ=0.1	5000	D.0.1	7-9
11	CCN	l_1 and r_1 change when μ=0.1	5000	D.0.1	9&11

Figure C.1: True Distribution of TN with bounds of [-2,2] and Fitted pdf Curves

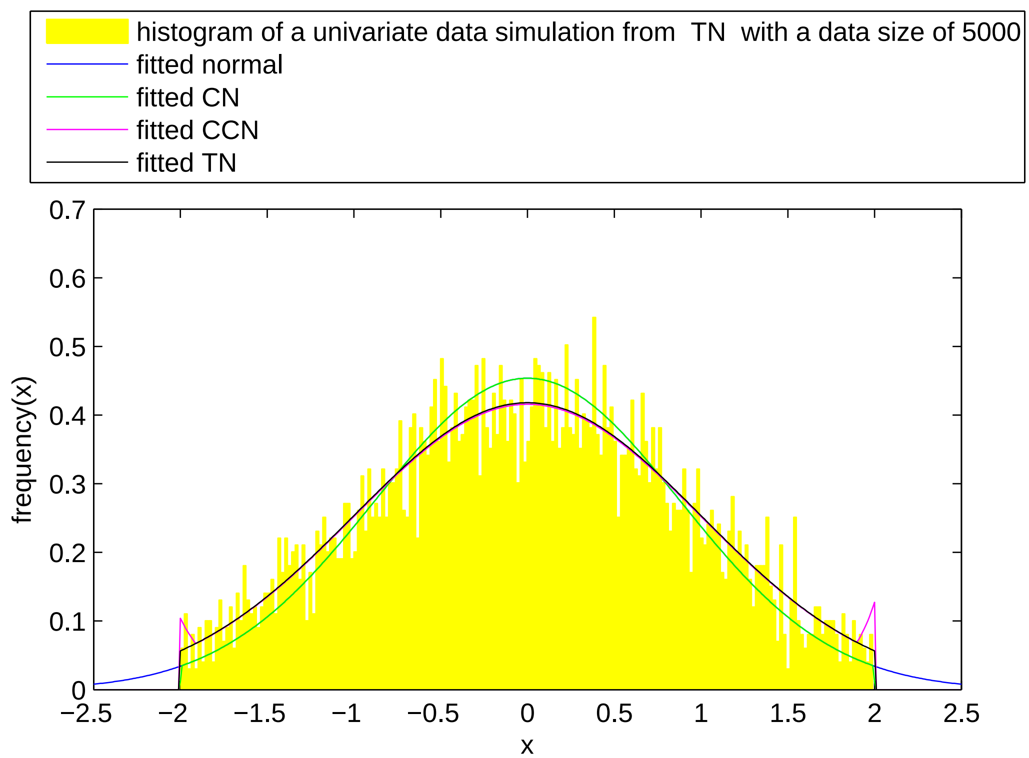


Figure C.2: True Distribution of CN with bounds of [-2,2] and Fitted pdf Curves

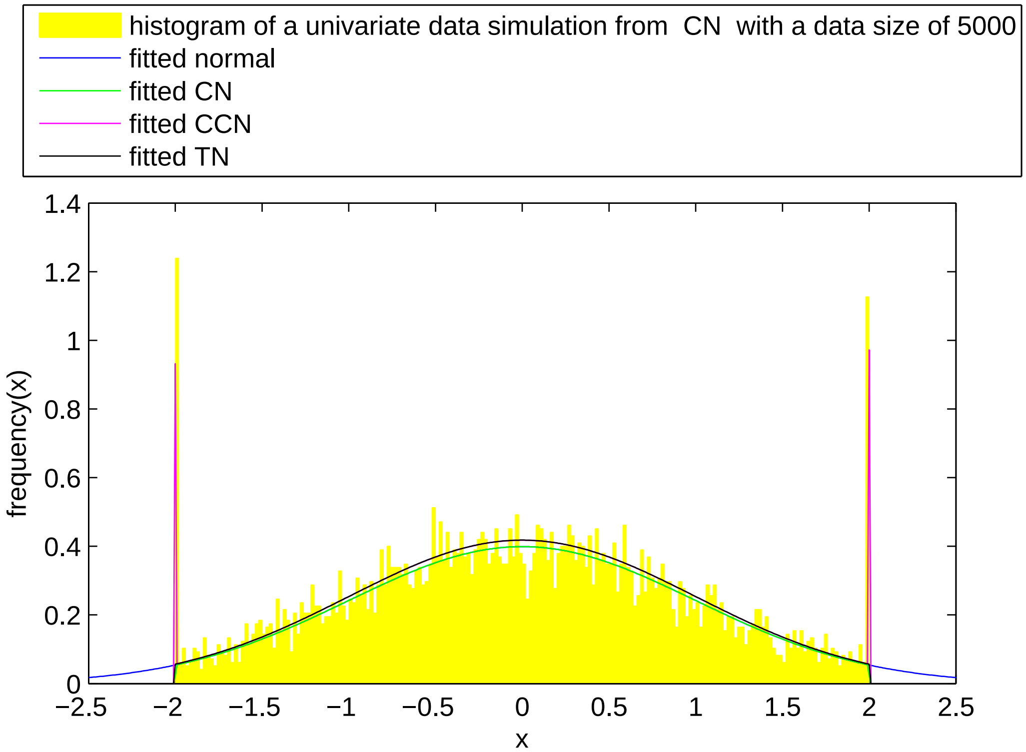


Figure C.3: True Distribution of CCN with bounds of [-2,2] and Fitted pdf Curves

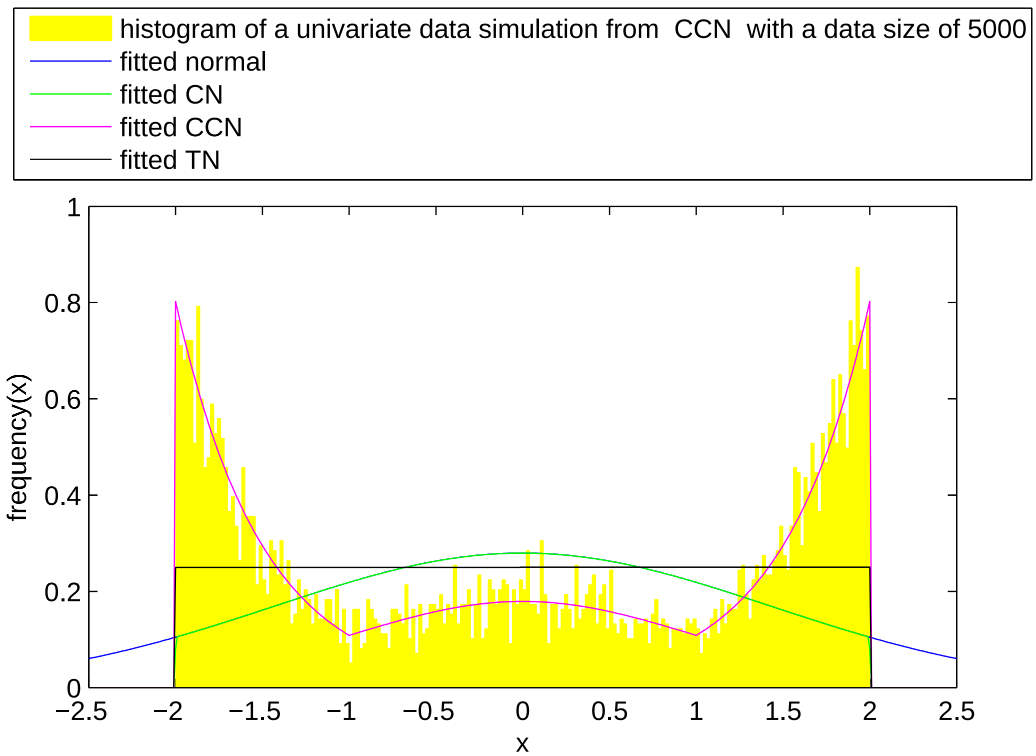


Table C.0.2: Results from Experiment 1 for TN

Bounds	Normal		TN		CN		CCN					
	μ	σ	μ	σ	μ	σ	μ	σ	l_1	r_1	m_1	m_2
$[-4, 4]$	-0.0008	0.9997***	-0.0008	1.0002***	-0.0008	0.9997***	-0.0009	0.9996***	0.9905***	1.0024***	-1.4221	0.8712
	(0.0139)	(0.0093)	(0.0139)	(0.0094)	(0.0139)	(0.0093)	(0.0139)	(0.0096)	(0.0581)	(0.1447)	(8.7876)	(3.2053)
$[-3, 3]$	0.0002	0.9865***	0.0010	0.9993***	0.0010	0.9859***	0.0012	0.9974***	0.9748***	0.9746***	-1.0854	1.2580
	(0.0137)	(0.0094)	(0.0134)	(0.0095)	(0.0137)	(0.0095)	(0.0140)	(0.0111)	(0.0429)	(0.0452)	(7.3087)	(6.4649)
$[-2, 2]$	0.0000	0.8799***	0.0001	1.0006***	0.0000	0.8798***	-0.0001	0.9970***	0.9691***	0.9721***	-0.2844	0.3505
	(0.0126)	(0.0073)	(0.0163)	(0.0156)	(0.0126)	(0.0073)	(0.0164)	(0.0156)	(0.0328)	(0.0373)	(2.8004)	(2.1387)

Notes: $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$

Real mean=0, Real standard deviation=1.

Table C.0.3: Results from Experiment 2 for TN

Bounds	Normal		TN		CN		CCN					
	μ	σ	μ	σ	μ	σ	μ	σ	l_1	r_1	m_1	m_2
$[-4, 4]$	-0.0011	0.9998***	-0.0011	0.9994***	-0.0011	0.9989***	-0.0010	0.9988***	1.0000***	1.0000***	-0.2379	0.2589
	(0.0453)	(0.0314)	(0.0454)	(0.0316)	(0.0453)	(0.0314)	(0.0455)	(0.0314)	(0.7744)	(1.5997)	(2.4520)	(1.1285)
$[-3, 3]$	-0.0003	0.9857***	-0.0003	0.9985***	-0.0003	0.9848***	0.0007	0.9922***	0.9748***	0.9899***	-20.2465	16.8953
	(0.0464)	(0.0303)	(0.0477)	(0.0346)	(0.0464)	(0.0302)	(0.0491)	(0.0347)	(0.0830)	(0.1658)	(157.5152)	(156.3750)
$[-2, 2]$	-0.0001	0.8794***	-0.0001	1.0011***	-0.0001	0.8785***	-0.0017	0.9817***	0.9553***	0.9487***	-4.9314	6.0292
	(0.0383)	(0.0244)	(0.0496)	(0.0532)	(0.0383)	(0.0243)	(0.0521)	(0.0571)	(0.0674)	(0.0690)	(21.4400)	(29.7312)

Notes: $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$

Real mean=0, Real standard deviation=1.

Table C.0.4: Results from Experiment 3 for CN

Bounds	Normal		TN		CN		CCN					
	μ	σ	μ	σ	μ	σ	μ	σ	l_1	r_1	m_1	m_2
$[-4, 4]$	0.0011	1.0002***	0.0011	1.0006***	0.0011	1.0002***	0.0011	1.0005***	0.9993***	0.9993***	-165.1612	374.1531
	(0.0139)	(0.0105)	(0.0139)	(0.0106)	(0.0139)	(0.0105)	(0.0143)	(0.0102)	(0.0667)	(0.0495)	(1.1014e+003)	(2.2310e+003)
$[-3, 3]$	0.0019	0.9955***	0.0019	1.0098***	0.0019	0.9970***	-0.0076	0.9993***	0.9993***	0.9073***	-1000	1030
	(0.0463)	(0.0319)	(0.0477)	(0.0368)	(0.0466)	(0.0328)	(0.0472)	(0.0356)	(0.0907)	(0.1024)	(1.6758e+004)	(4.9602e+003)
$[-2, 2]$	0.0006	0.9599***	0.0010	1.2170***	0.0006	1.0007***	-0.0063	1.0000***	0.9993***	0.9993***	-2000	2010
	(0.0128)	(0.0081)	(0.0206)	(0.0278)	(0.0133)	(0.1405)	(0.0521)	(0.1597)	(0.2276)	(0.1887)	(5.0849e+003)	(4.6664e+003)

Notes: $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$
Real mean=0, Real standard deviation=1.

Table C.0.5: Results from Experiment 4 for CN

Bounds	Normal		TN		CN		CCN					
	μ	σ	μ	σ	μ	σ	μ	σ	l_1	r_1	m_1	m_2
$[-4, 4]$	-0.0001	1.0011***	-0.0001	1.0007***	-0.0001	1.0002***	-0.0010	1.0001***	1.0000***	0.9894***	-0.0179	0.1941
	(0.0474)	(0.0327)	(0.0475)	(0.0330)	(0.0474)	(0.0327)	(0.0401)	(0.0377)	(1.1292e-005)	(0.0491)	(0.9466)	(0.5224)
$[-3, 3]$	-0.0009	0.9939***	-0.0010	1.0080***	-0.0009	0.9955***	-0.0059	0.9877***	0.9914***	0.9931***	-841.9550	860.7989
	(0.0433)	(0.0342)	(0.0447)	(0.0392)	(0.0435)	(0.0348)	(0.0423)	(0.0383)	(0.0909)	(0.0800)	(3.5627e+003)	(963.8479)
$[-2, 2]$	-0.0029	0.9576***	-0.0041	1.2141***	-0.0026	0.9970***	-0.0020	1.0507***	0.9931***	0.9950***	-2301.3	2109.8
	(0.0464)	(0.0246)	(0.0751)	(0.0851)	(0.0485)	(0.0310)	(0.1504)	(0.2701)	(0.1816)	(0.2162)	(5.3034e+003)	(6.1347e+003)

Notes: $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$
Real mean=0, Real standard deviation=1.

Table C.0.6: Results from Experiment 5 for CCN with repect to bounds

pm	Bounds	Normal		TN		CN		CCN					
		μ	σ	μ	σ	μ	σ	μ	σ	l_1	r_1	m_1	m_2
0.9990	$[-12, 12]$	-0.0006	1.0585***	-0.0001	1.0614***	-0.0001	1.0614***	-0.0005	0.9998***	0.5497***	0.5444***	-3.7780	3.8158
		(0.0136)	(0.0307)	(0.0141)	(0.0282)	(0.0141)	(0.0282)	(0.0131)	(0.0099)	(0.1117)	(0.1144)	(4.6015)	(7.0786)
0.9683	$[-10, 10]$	0.0011	1.9525***	-0.0020	0.9564***	0.0011	1.9525***	-0.0020	1.9564***	0.5035***	0.5010***	-2.0495***	2.0180***
		(0.0275)	(0.0595)	(0.0274)	(0.0578)	(0.0274)	(0.0578)	(0.0146)	(0.0112)	(0.0162)	(0.0163)	(0.2458)	(0.2518)
0.3586	$[-6, 6]$	-0.0041	4.4677***	11.9400	$2.7042e + 05$	0.0002	4.4651***	0.0007	1.0004***	0.5001***	0.4996***	-2.0031***	1.9943***
		(0.0696)	(0.0251)	(4.6979e+03)	(3.9575e+05)	(0.0664)	(0.0218)	(0.0255)	(0.0185)	(0.0071)	(0.0071)	(0.0536)	(0.0554)
0.2765	$[-5, 5]$	-0.0015	3.8958***	170.3752	$3.0681e + 05$	0.0035	3.8942***	-0.0010	0.9996***	0.4996***	0.4999***	-1.9993***	2.0038***
		(0.0530)	(0.0201)	(3.7763e+03)	(3.9570e+05)	(0.0575)	(0.0168)	(0.0201)	(0.0235)	(0.0089)	(0.0081)	(0.0533)	(0.0506)
0.2480	$[-4, 4]$	0.0018	3.1189***	-65.2269	$2.1180e + 05$	-0.0033	3.1197***	0.0013	1.0018***	0.4993***	0.4997***	-1.9938***	1.9951***
		(0.0460)	(0.0123)	(2.7333e+03)	(2.6794e+05)	(0.0418)	(0.0131)	(0.0330)	(0.0335)	(0.0106)	(0.0095)	(0.0551)	(0.0549)
0.2595	$[-3, 3]$	-0.0008	2.2720***	324.8356	$1.4705e + 05$	0.0054	2.2697***	-0.0007	1.0013***	0.5000***	0.4989***	-2.0037***	1.9942***
		(0.0316)	(0.0099)	(2.0951e+03)	(1.9877e+05)	(0.0310)	(0.0082)	(0.0379)	(0.0476)	(0.0118)	(0.0120)	(0.0644)	(0.0623)
0.3063	$[-2, 2]$	0.0018	1.4280***	-68.4227	$9.0980e + 04$	-0.0016	1.4290***	0.0015	0.9989***	0.4987***	0.4988***	-1.9977***	1.9998***
		(0.0212)	(0.0063)	(1.8729e+03)	(1.4487e+05)	(0.0192)	(0.0071)	(0.0496)	(0.0855)	(0.0167)	(0.0177)	(0.0913)	(0.0875)

Notes: $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$
Real mean=0, Real standard deviation=1.
$m_1 = -2$, $m_2 = 2$; Real clustering rate=0.5

Table C.0.7: Results from Experiment 6 for CCN with respect to $m_1\&m_2$

pm	$m_1\&m_2$	Normal		TN		CN		CCN					
		μ	σ	μ	σ	μ	σ	μ	σ	l_1	r_1	m_1	m_2
0.3063	$-2\&2$	0.0018	1.4280^{***}	-68.4227	$9.0980e+04$	-0.0016	1.4290^{***}	0.0015	0.9989^{***}	0.4987^{***}	0.4988^{***}	-1.9977^{***}	1.9998^{***}
		(0.0316)	(0.0099)	(2.0951e+03)	(1.9877e+05)	(0.0310)	(0.0082)	(0.0379)	(0.0476)	(0.0118)	(0.0120)	(0.0644)	(0.0623)
0.4508	$-1\&1$	-0.0006	1.8345^{***}	349.2766	$1.0326e+005^{***}$	0.0030	1.8353^{***}	0.0014	1.0026^{***}	0.5007^{***}	0.5007^{***}	-1.0037^{***}	0.9983^{***}
		(0.0263)	(0.0116)	(3.9911e+003)	(5.1370e+004)	(0.0256)	(0.0115)	(0.0277)	(0.0378)	(0.0141)	(0.0164)	(0.0678)	(0.0755)
0.6320	$0.3\&-0.3$	-0.0001	1.3163^{***}					-0.0004	0.9982^{***}	0.4986^{***}	0.4993^{***}	0.2925^{***}	-0.2900^{***}
		(0.0182)	(0.0124)					(0.0218)	(0.0314)	(0.0329)	(0.0292)	(0.1106)	(0.0955)
0.6906	$1\&-1$	-0.0008	1.1338^{***}					-0.0025	0.9979^{***}	0.4887^{***}	0.4987^{***}	0.9736^{***}	-0.9581^{***}
		(0.0159)	(0.0108)					(0.0213)	(0.0273)	(0.0867)	(0.0686)	(0.1287)	(0.1216)
0.7654	$2\&-2$	0.0001	0.9789^{***}					-0.0017	1.0100^{***}	0.5136^{***}	0.5340^{***}	1.9714^{*}	-2.0808^{***}
		(0.0133)	(0.0105)					(0.0207)	(0.0306)	(0.0975)	(0.1543)	(0.9135)	(0.3957)

Notes: $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$
Real mean=0, Real standard deviation=1.
Real clustering rate=0.5. Bounds [-3,3]

Table C.0.8: Esitmates from CCN simulations: l_1 and r_1

pm	l_1&r_1	Normal		CCN					
		μ	σ	μ	σ	l_1	r_1	m_1	m_2
0.0346	0.2	0.0022	2.5457***	-0.0099	0.9295**	0.1990***	0.1968***	−2.0073***	2.0057***
		(0.0362)	(0.0056)	(0.3380)	(0.3532)	(0.0315)	(0.0351)	(0.0428)	(0.0442)
0.3063	0.5	0.0018	1.4280***	-0.0007	1.0013***	0.5000***	0.4989***	−2.0037***	1.9942***
		(0.0316)	(0.0099)	(0.0379)	(0.0476)	(0.0118)	(0.0120)	(0.0644)	(0.0623)
0.5007	0.6	-0.0025	1.8905***	-0.0003	1.0009***	0.5995***	0.6004***	−1.9958***	2.0037***
		(0.0252)	(0.0122)	(0.0245)	(0.0274)	(0.0115)	(0.0104)	(0.1043)	(0.0911)
0.8676	0.8	-0.0003	1.1088***	-0.0006	0.9978***	0.7987***	0.7992***	−2.0487***	2.0704***
		(0.0152)	(0.0119)	(0.0155)	(0.0134)	(0.0193)	(0.0181)	(0.5940)	(0.5766)

Notes: $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$
Real mean=0, Real standard deviation=1.
$m_1 = -2$, and $m_2 = 2$. Bounds [-3,3]

Appendix D

Results from Monte Carlo Simulations for CCN models with a data size of 500 and Plots of pdfs of CCN if 1. only bounds change; 2. only clustering rates change; 3. only clustering coefficients change

Figure D.1: Comparison of $variance - b$ among CN, TN, and CCN

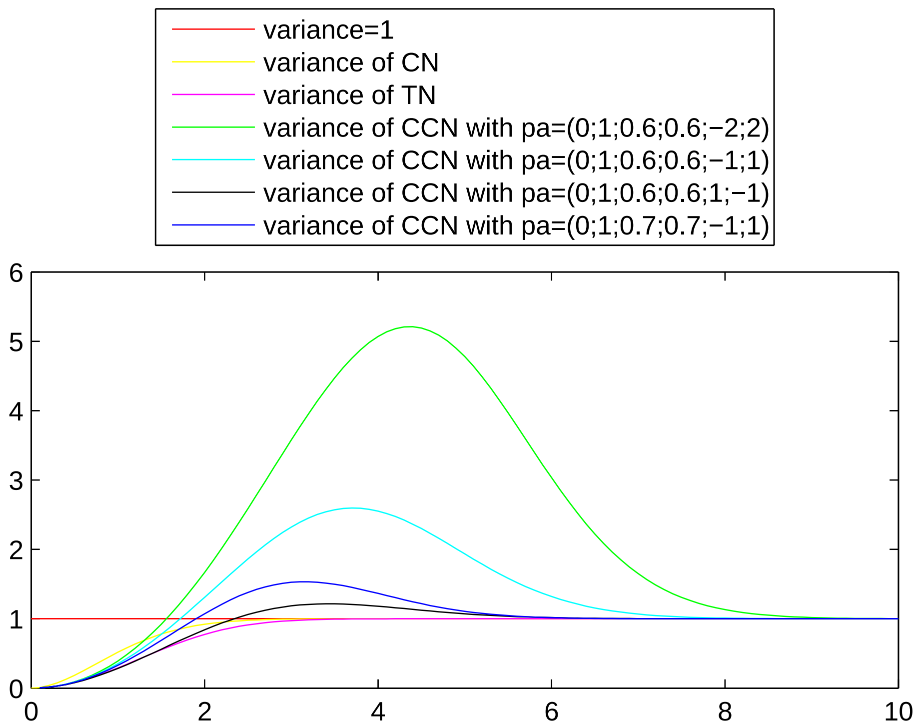


Figure D.2: Comparison of $kurtosis - b$ among CN, TN, and CCN

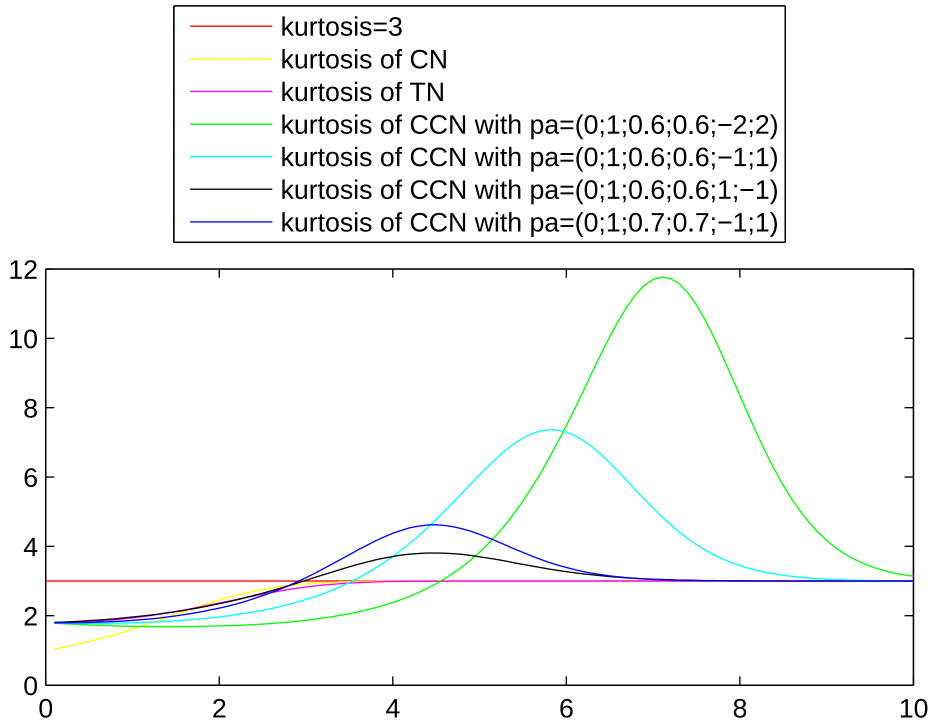


Table D.0.1: Esitmates from Asymmetric simulations

Row No.										
1	true model	μ	σ	domains						
	TN	0.1	1	[-2,2]						
	normal	μ	σ	TN	μ	σ				
		0.0767***	0.8785***		0.0992***	1.0001***				
		(0.0125)	(0.0079)		(0.0162)	(0.0169)				
2	true model	μ	σ	domains						
	TN	0.1	1	[-3,3]						
	normal	μ	σ	TN	μ	σ				
		0.0973***	0.9857***		0.1000***	0.9994***				
		(0.0141)	(0.0091)		(0.0145)	(0.0104)				
3	true model	μ	σ	domains						
	TN	0.1	1	[-4,4]						
	normal	μ	σ	TN	μ	σ				
		0.0990***	0.9997***		0.0991***	1.0002***				
		(0.0140)	(0.0094)		(0.0140)	(0.0095)				
4	true model	μ	σ	domains						
	CN	0.1	1	[-2,2]						
	normal	μ	σ	CN	μ	σ				
		0.0964***	0.9583***		0.1010***	0.9997***				
		(0.0133)	(0.0087)		(0.0139)	(0.0111)				
5	true model	μ	σ	domains						
	CN	0.1	1	[-3,3]						
	normal	μ	σ	CN	μ	σ				
		0.1001***	0.9986***		0.1003***	1.0012***				
		(0.0138)	(0.0098)		(0.0139)	(0.0101)				
6	true model	μ	σ	domains						
	CN	0.1	1	[-4,4]						
	normal	μ	σ	CN	μ	σ				
		0.1000***	1.0007***		0.1000***	1.0007***				
		(0.0138)	(0.0096)		(0.0139)	(0.0096)				
	true model	μ	σ	l_1	r_1	m_1	m_2	domains	pm	
7	CCN	0.1	1	0.5	0.5	0.3	-0.3	[-3,3]	0.7330	
	normal	μ	σ	CCN	μ	σ	l_1	r_1	m_1	m_2
		0.1261***	1.3124***		0.0977***	0.9981***	0.4997***	0.4974***	0.2950***	−0.2988***
		(0.0185)	(0.0122)		(0.0241)	(0.0300)	(0.0273)	(0.0340)	(0.0983)	(0.0934)
8	CCN	0.1	1	0.5	0.5	-1	1	[-3,3]	0.4879	
	normal	μ	σ	CCN	μ	σ	l_1	r_1	m_1	m_2
		0.2132***	1.8262***		0.0982***	1.0036***	0.5027***	0.5000***	−1.0103***	0.9996***
		(0.0265)	(0.0117)		(0.0274)	(0.0372)	(0.0151)	(0.0138)	(0.0773)	(0.0653)
9	CCN	0.1	1	0.5	0.5	-2	2	[-3,3]	0.2765	
	normal	μ	σ	CCN	μ	σ	l_1	r_1	m_1	m_2
		0.2986***	2.2548***		0.0963**	0.9965***	0.4996***	0.4981***	−2.0043***	1.9992***
		(0.0324)	(0.0112)		(0.0393)	(0.0513)	(0.0138)	(0.0126)	(0.0731)	(0.0642)
10	CCN	0.1	1	0.5	0.5	-2	2	[-2,2]	0.4923	
	normal	μ	σ	CCN	μ	σ	l_1	r_1	m_1	m_2
		0.1225***	1.4238***		0.0992**	1.0013***	0.4989***	0.4995***	−2.0012***	2.0070***
		(0.0200)	(0.0067)		(0.0496)	(0.1019)	(0.0200)	(0.0178)	(0.0990)	(0.0885)
11	CCN	0.1	1	0.7	0.7	-2	2	[-3,3]	0.8101	
	normal	μ	σ	CCN	μ	σ	l_1	r_1	m_1	m_2
		0.1708***	1.4149***		0.1021***	0.9996***	0.6995***	0.7016***	−2.0113***	2.0280***
		(0.0181)	(0.0132)		(0.0168)	(0.0171)	(0.0129)	(0.0110)	(0.2311)	(0.1798)

Notes: $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$

Table D.0.2: Results from Experiment 8 for CCN with repect to bounds (data size: 500)

pm	Bounds	Normal		TN		CN		CCN					
		μ	σ	μ	σ	μ	σ	μ	σ	l_1	r_1	m_1	m_2
0.9990	$[-12, 12]$	-0.0042	1.0583***	-0.0044	1.0635***	-0.0044	1.0635***	-0.0014	0.9998***	0.6071***	0.5766**	-1.7385	2.1277
		(0.0472)	(0.0925)	(0.0506)	(0.0895)	(0.0506)	(0.0895)	(0.0355)	(0.0356)	(0.1841)	(0.2067)	(11.1676)	(18.9930)
0.9683	$[-10, 10]$	0.0068	1.9551***	0.0023	1.9473***	0.0023	1.9472***	0.0101	0.9971***	0.5097***	0.5129***	-2.2772**	2.3304*
		(0.0786)	(0.1676)	(0.0923)	(0.1887)	(0.0923)	(0.1889)	(0.0439)	(0.0308)	(0.0497)	(0.0538)	(0.8996)	(1.0538)
0.3586	$[-6, 6]$	-0.0072	4.4667***	-284.0407	$1.0521e+005$	0.0120	4.4600***	-0.0072	0.9900***	0.4976***	0.4974***	-2.0087***	2.0212***
		(0.1902)	(0.0759)	(4.5679e+003)	(3.0682e+005)	(0.1948)	(0.0501)	(0.0759)	(0.0586)	(0.0215)	(0.0223)	(0.1748)	(0.1786)
0.2765	$[-5, 5]$	0.0058	3.8939***	254.2409	$8.3366e+004$	-0.0088	3.8914***	-0.0011	0.9961***	0.4982***	0.4979***	-2.0048***	2.0063***
		(0.1732)	(0.0573)	(3.6071e+003)	(2.4023e+005)	(0.1680)	(0.0525)	(0.0936)	(0.0728)	(0.0248)	(0.0275)	(0.1644)	(0.1681)
0.2480	$[-4, 4]$	-0.0125	3.1198***	108.6379	$7.7524e+004$	0.0125	3.1169***	0.0026	0.9961***	0.4963***	0.4965***	-2.0060***	1.9974***
		(0.1417)	(0.0396)	(2.7268e+003)	(2.0088e+005)	(0.1436)	(0.0431)	(0.1038)	(0.1081)	(0.0310)	(0.0316)	(0.1870)	(0.1838)
0.2595	$[-3, 3]$	0.0620	2.2670***	-206.9143	$7.1812e+004$	-0.0002	2.2715***	-0.0582	1.2135***	0.4479***	0.5704***	-2.0407***	2.2425***
		(0.1014)	(0.0718)	(2.2085e+003)	(1.6997e+005)	(0.0912)	(0.0292)	(0.1088)	(0.1045)	(0.0292)	(0.0203)	(0.0982)	(0.0912)
0.3063	$[-2, 2]$	-0.0079	1.4270***	39.2987	$2.6142e+004$	0.0025	1.4275***	-0.0075	0.9347***	0.4883***	0.4836***	-2.0377***	2.0020***
		(0.0622)	(0.0201)	(1.4881e+003)	(7.2900e+004)	(0.0615)	(0.0213)	(0.1277)	(0.2097)	(0.0531)	(0.0505)	(0.2794)	(0.2824)

Notes: $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$
Real mean=0, Real standard deviation=1.
$m_1 = -2$, and $m_2 = 2$. Real clustering rate=0.5.

Table D.0.3: Estimates from CCN simulations: $m_1\&m_2$ (data size: 500)

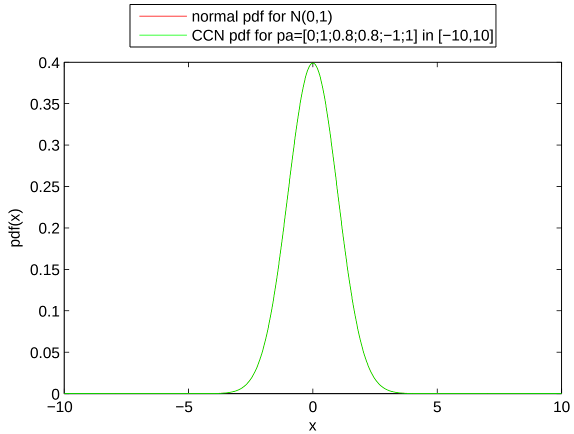
pm	$m_1\&m_2$	Normal		CCN					
		μ	σ	μ	σ	l_1	r_1	m_1	m_2
0.3063	$-2\&2$	-0.0079	1.4270***	-0.0075	0.9347***	0.4883***	0.4836***	-2.0377***	2.0020***
		(0.0622)	(0.0201)	(0.1277)	(0.2097)	(0.0531)	(0.0505)	(0.2794)	(0.2824)
0.4508	$-1\&1$	-0.0115	1.8343***	0.0018	1.0080***	0.4947***	0.5004***	-0.9964***	1.0102***
		(0.0773)	(0.0390)	(0.0875)	(0.1375)	(0.0544)	(0.0475)	(0.2374)	(0.2361)
0.6320	$0.3\&-0.3$	-0.0072	1.3121***	-0.0020	0.9691***	0.4770***	0.4917***	0.2356	-0.2347
		(0.0620)	(0.0381)	(0.0667)	(0.1130)	(0.1091)	(0.1105)	(0.3573)	(0.2749)
0.6906	$1\&-1$	0.0038	1.1325***	-0.0011	0.9975***	0.5207**	0.4851***	0.8964	-0.8087
		(0.0521)	(0.0334)	(0.0668)	(0.1267)	(0.2113)	(0.1534)	(0.9896)	(0.7260)
0.7654	$2\&-2$	0.0003	0.9765***	-0.0056	1.0616***	0.5246*	0.5301**	0.3984	-6.7339
		(0.0453)	(0.0303)	(0.0528)	(0.1555)	(0.2359)	(0.2169)	(30.6837)	(51.8943)

Notes: $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$
Real mean=0, Real standard deviation=1.
Real clustering rate=0.5. Bounds [-3,3]
1000 simulations with a data size of 500.

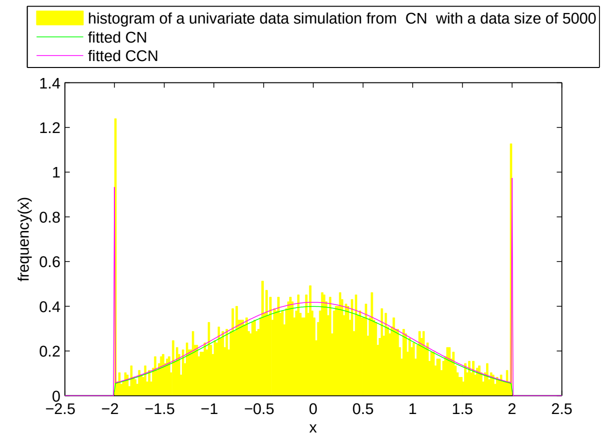
Table D.0.4: Estimates from CCN simulations: l_1 and r_1 (data size: 500)

pm	l_1&r_1	Normal		CCN					
		μ	σ	μ	σ	l_1	r_1	m_1	m_2
0.0346	0.2	-0.0036	2.5456***	-0.0274	1.0041**	0.1809***	0.1604***	-2.0166***	1.9893***
		(0.1181)	(0.0186)	(0.2733)	(0.4121)	(0.1000)	(0.1227)	(0.1425)	(0.1537)
0.3063	0.5	-0.0079	1.4270***	-0.0075	0.9347***	0.4883***	0.4836***	-2.0377***	2.0020***
		(0.0622)	(0.0201)	(0.1277)	(0.2097)	(0.0531)	(0.0505)	(0.2794)	(0.2824)
0.5007	0.6	0.0047	1.8869***	-0.0006	0.9969***	0.6008***	0.5999***	-2.0461***	2.0428***
		(0.0894)	(0.0414)	(0.0759)	(0.0858)	(0.0335)	(0.0362)	(0.3346)	(0.3380)
0.8676	0.8	0.0016	1.1111***	0.0029	0.9947***	0.8012***	0.7939***	-2.7845	2.1486
		(0.0497)	(0.0376)	(0.0477)	(0.0434)	(0.0541)	(0.0627)	(3.3232)	(2.6254)

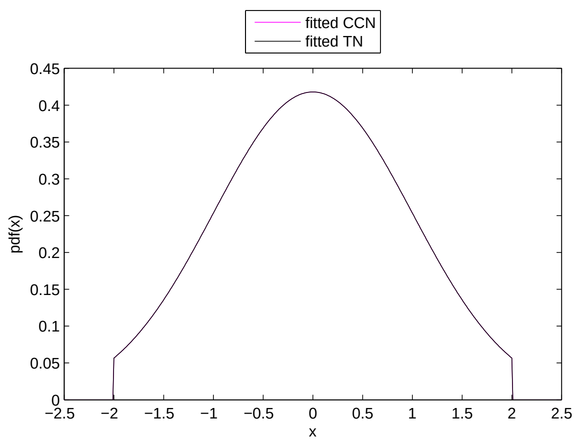
Notes: $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$
Real mean=0, Real standard deviation=1.
$m_1 = -2$, and m_2=2. Bounds [-3,3]



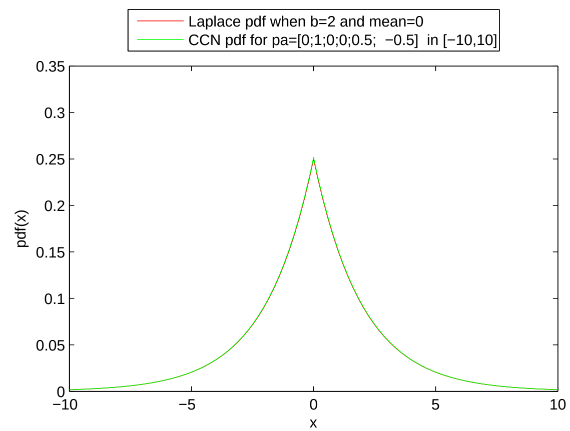
(a) *Normal*



(b) *CN*



(c) *TN*



(d) *Laplace*

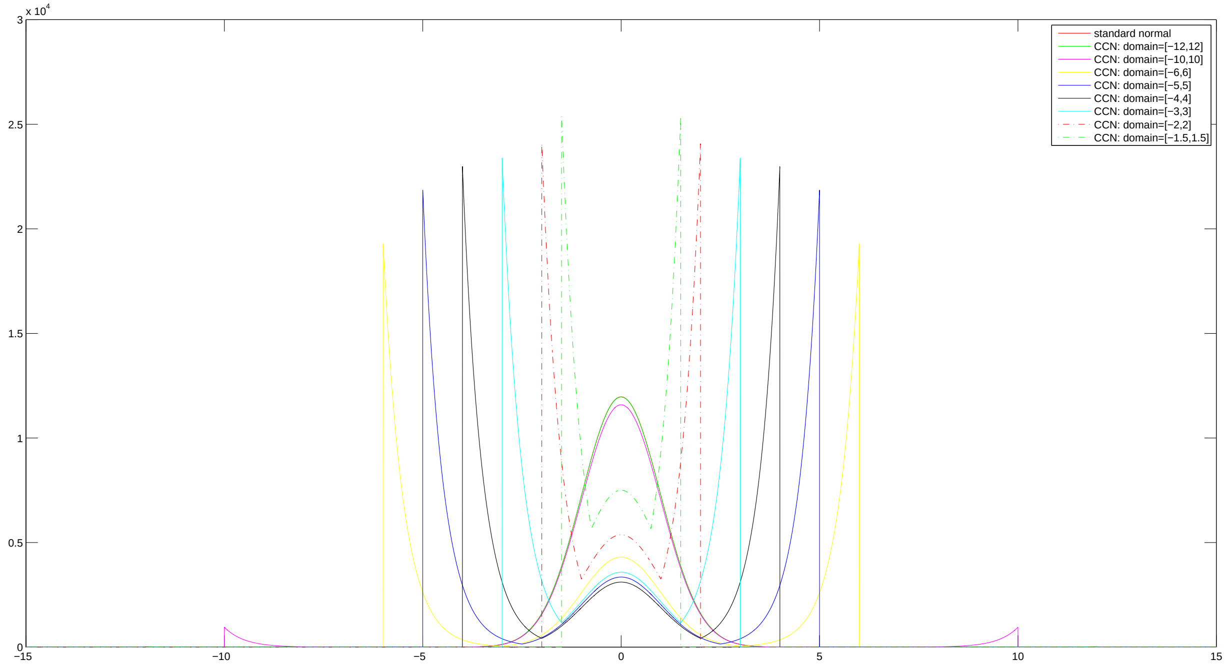


Figure D.4: pdfs of CCN if only bounds change($\mu = 0$, $\sigma = 1$, $m_1 = -2$, $m_2 = 2$, and l_1=$r_1 = 0.5$)

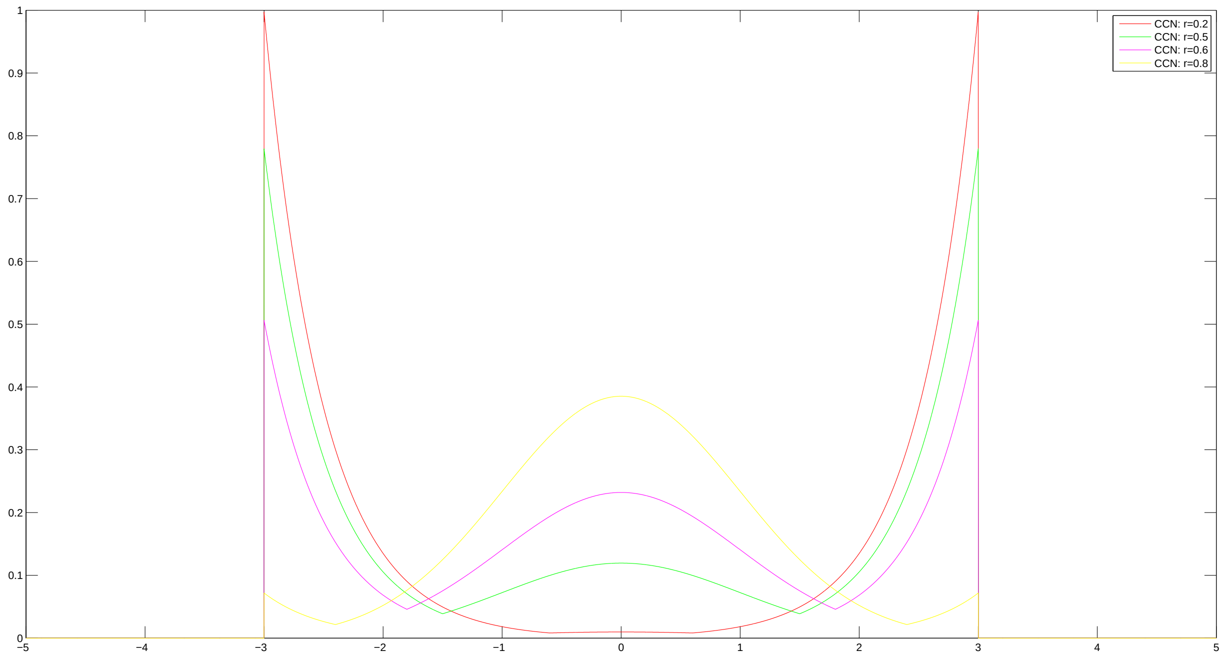


Figure D.5: pdfs of CCN if only l_1 and r_1 change ($\mu = 0$, $\sigma = 1$, $m_1 = -2$, $m_2 = 2$, and domain= $[-3, 3]$, l_1=r_1=r)

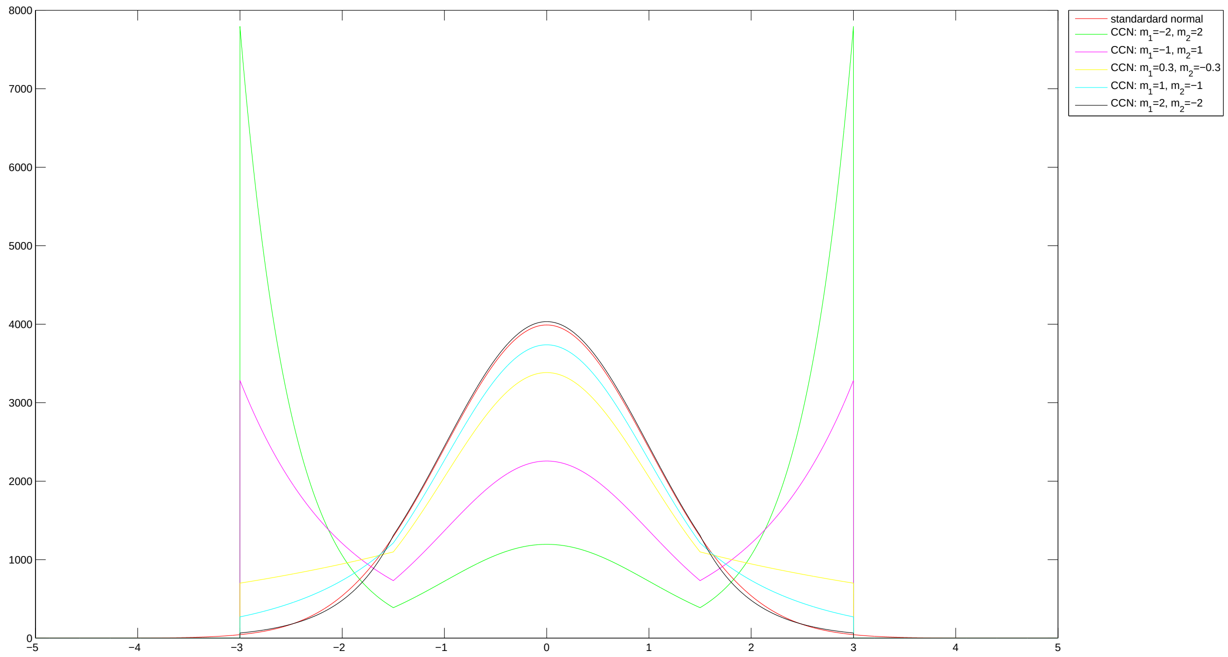


Figure D.6: pdfs of CCN if only m_1 and m_2 change ($\mu = 0$, $\sigma = 1$, l_1=$r_1 = 0.5$, and domain= $[-3, 3]$)

Appendix E

Empirical Performances of Normal, CN, TN, and CCN for 5 Taiwanese stocks, 5 Chinese stocks, 5 Korean stocks, and 5 French stocks

Table E.0.3: Empirical comparison of normal, CN, TN, and CCN

Moments/Parameters	Data	Four Models			
5 Taiwanese Stocks (daily limit of 7%)					
	TaiFlex	normal	TN	CN	CCN
μ		-0.0186	-0.0018	-0.0187	0.0407
		(0.0707)	(0.0710)	(0.0967)	(0.0449)
σ		2.5834***	2.6770***	2.5824***	2.2024***
		(0.0500)	(0.0575)	(0.0500)	(0.0499)
l_1					0.7306***
					(0.0209)
r_1					0.9357***
					(0.0094)
m_1					−0.6138**
					(0.2137)
m_2					9.8839***
					(1.9981)
-LOGL		3.1656e+003	3.1551e+003	3.1656e+003	3.0587e+003
AIC		6.3351e+003	6.3141e+003	6.3351e+003	6.1294e+003
BIC		6.3455e+003	6.3245e+003	6.3455e+003	6.1318e+003
pm					0.9439
	Tung Kai	normal	TN	CN	CCN
μ		−0.1124*	-0.0605	−0.1020**	−0.0284***
		(0.0615)	(0.0624)	(0.0555)	(0.0154)
σ		3.2226***	3.4942***	3.0773***	2.1026***
		(0.0435)	(0.0726)	(0.0417)	(0.0345)
l_1					0.7452***
					(0.0109)
r_1					0.8456***
					(0.0077)
m_1					−1.5100***
					(0.1515)
m_2					4.1203***
					(0.3182)
-LOGL		6.9220e+003	6.8371e+003	6.9220e+003	6.2911e+003
AIC		1.3848e+004	1.3678e+004	1.3848e+004	1.2594e+004

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Table E.0.3 – continued from previous page

Moments/Parameters	Data	Four Models			
BIC		1.3860e+004	1.3690e+004	1.3860e+004	1.2630e+004
pm					0.8659
	Tri Ocean Textile	normal	TN	CN	CCN
μ		0.0329	0.0625	0.0083	-0.2170^{***}
		(0.0462)	(0.0467)	(0.0077)	(0.0357)
σ		2.7018^{***}	2.8431^{***}	2.6243^{***}	1.9819^{***}
		(0.0327)	(0.0401)	(0.0318)	(0.0276)
l_1					0.7727^{***}
					(0.0128)
r_1					0.7815^{***}
					(0.0088)
m_1					-1.4498^{***}
					(0.2200)
m_2					2.3832^{***}
					(0.1851)
-LOGL		8.2466e+003	8.2065e+003	8.1635e+003	7.6949e+003
AIC		1.6497e+004	1.6417e+004	1.6497e+004	1.5402e+004
BIC		1.6510e+004	1.6429e+004	1.6497e+004	1.5439e+004
pm					0.9087
	Jye Tai Precision	normal	TN	CN	CCN
μ		-0.0138	0.0071	-0.0132	-0.1595^{***}
		(0.0515)	(0.0519)	(0.0144)	(0.0389)
σ		2.6496^{***}	2.7676^{***}	2.6509^{***}	1.8723^{***}
		(0.0364)	(0.0433)	(0.0365)	(0.0288)
l_1					0.7233^{***}
					(0.0138)
r_1					0.8522^{***}
					(0.0085)
m_1					-1.1869^{***}
					(0.1802)
m_2					5.2206^{***}
					(0.4524)
-LOGL		6.3299e+003	6.3039e+003	6.3301e+003	5.7803e+003
AIC		1.2664e+004	1.2612e+004	1.2664e+004	1.1573e+004
BIC		1.2676e+004	1.2624e+004	1.2676e+004	1.1608e+004
pm					0.9104
	Nan Kang Rubb Tire	normal	TN	CN	CCN
μ		-0.0106	0.0091	-0.0106	0.0096
		(0.0459)	(0.0461)	(0.0073)	(0.0076)
σ		2.6226^{***}	2.7308^{***}	2.6222^{***}	1.3424^{***}
		(0.0324)	(0.0381)	(0.0324)	(0.0269)
l_1					0.3484^{***}
					(0.0081)
r_1					0.3705^{***}
					(0.0085)
m_1					0.1650^{***}
					(0.0312)
m_2					-0.1226^{***}
					(0.0336)
-LOGL		7.7875e+003	7.7581e+003	7.7875e+003	7.4064e+003
AIC		1.5579e+004	1.5520e+004	1.5579e+004	1.4825e+004
BIC		1.5591e+004	1.5532e+004	1.5591e+004	1.4861e+004
pm					0.7353
5 Chinese Stocks (daily limit of 10%)					
	China Min-Sheng Bank	normal	TN	CN	CCN
μ		0.0519	0.0520	0.0519	0.0106
		(0.0400)	(0.0400)	(0.0446)	(0.2309)
σ		2.2556^{***}	2.2555^{***}	2.2552^{***}	1.5452^{***}
		(0.0283)	(0.0283)	(0.0283)	(0.1879)
l_1					0.2619^{***}
					(0.0236)
r_1					0.0532^{***}
					(0.0120)
m_1					-0.6001^{***}
					(0.0415)
m_2					-0.5675^{***}

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Table E.0.3 – continued from previous page

Moments/Parameters	Data	Four Models			
					(0.0275)
-LOGL		7.0805e+003	7.0804e+003	7.0805e+003	6.8839e+003
AIC		1.4165e+004	1.4165e+004	1.4165e+004	1.3780e+004
BIC		1.4177e+004	1.4177e+004	1.4177e+004	1.3816e+004
pm					0.5463
	China Merchants Energy Shipping	normal	TN	CN	CCN
μ		-0.0871 (0.0608)	-0.0865 (0.0608)	-0.0871 (0.0829)	0.0972* (0.0578)
σ		2.5720*** (0.0430)	2.5736*** (0.0432)	2.5713*** (0.0430)	1.9671*** (0.0385)
l_1					0.3839*** (0.0139)
r_1					0.7106*** (0.0251)
m_1					0.3339*** (0.0488)
m_2					1.1790*** (0.3219)
-LOGL		4.2233e+003	4.2231e+003	4.2233e+003	4.0706e+003
AIC		8.4506e+003	8.4502e+003	8.4506e+003	8.1533e+003
BIC		8.4616e+003	8.4612e+003	8.4616e+003	8.1862e+003
pm					0.9289
	Beijing North Star	normal	TN	CN	CCN
μ		-0.0645 (0.0687)	-0.0608 (0.0687)	-0.0636 (0.2555)	0.0017 (0.0116)
σ		2.9277*** (0.0486)	2.9400*** (0.0495)	2.9330*** (0.0488)	1.9101*** (0.0402)
l_1					0.4467*** (0.0116)
r_1					0.4056*** (0.0143)
m_1					0.0005*** (0.0356)
m_2					−0.2948*** (0.0487)
-LOGL		4.5271e+003	4.5258e+003	4.5279e+003	4.3148e+003
AIC		9.0582e+003	9.0556e+003	9.0598e+003	8.6416e+003
BIC		9.0692e+003	9.0666e+003	9.0708e+003	8.6746e+003
pm					0.8800
	GD Power Development	normal	TN	CN	CCN
μ		0.0436 (0.0516)	0.0439 (0.0515)	0.0436 (0.0727)	0.0566 (0.0849)
σ		2.3769*** (0.0365)	2.3770*** (0.0365)	2.3763*** (0.0364)	1.8935*** (0.0373)
l_1					0.3857*** (0.0146)
r_1					0.4342*** (0.0165)
m_1					0.4576*** (0.0605)
m_2					−0.4442*** (0.0700)
-LOGL		4.8545e+003	4.8545e+003	4.8545e+003	4.7583e+003
AIC		9.7131e+003	9.7129e+003	9.7131e+003	9.5286e+003
BIC		9.7244e+003	9.7242e+003	9.7244e+003	9.5625e+003
pm					0.9209
	Inner Mongolia Baotou Steel Union	normal	TN	CN	CCN
μ		-0.0243 (0.0455)	-0.0237 (0.0455)	-0.0239 (0.0169)	0.0180 (0.0241)
σ		2.5198*** (0.0322)	2.5212*** (0.0323)	2.5209*** (0.0322)	1.8224*** (0.0297)
l_1					0.3362***

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Table E.0.3 – continued from previous page

Moments/Parameters	Data	Four Models			
					(0.0105)
r_1					0.4811***
					(0.0124)
m_1					0.4651***
					(0.0371)
m_2					−0.0748***
					(0.0607)
-LOGL		7.1788e+003	7.1786e+003	7.1798e+003	6.9303e+003
AIC		1.4362e+004	1.4361e+004	1.4364e+004	1.3873e+004
BIC		1.4374e+004	1.4373e+004	1.4376e+004	1.3909e+004
pm					0.9008
5 Korean Stocks (daily limit of 15%)					
	Shin Woo Co., Ltd.	normal	TN	CN	CCN
μ		-0.1081	-0.0309	−0.0974*	−0.2990***
		(0.0945)	(0.0946)	(0.0604)	(0.0661)
σ		5.7677***	5.7220***	5.5969***	3.6792***
		(0.0669)	(0.0775)	(0.0679)	(0.0495)
l_1					0.5948***
					(0.0115)
r_1					0.9252***
					(0.0045)
m_1					−0.1951***
					(0.0384)
m_2					7.3313***
					(0.5411)
-LOGL		1.0816e+004	1.0786e+004	1.0796e+004	9.8389e+003
AIC		2.1636e+004	2.1576e+004	2.1596e+004	1.9690e+004
BIC		2.1648e+004	2.1589e+004	2.1609e+004	1.9727e+004
pm					0.9006
	Borneo International Furniture BIF Co Ltd	normal	TN	CN	CCN
μ		-0.0502	-0.0390	-0.0468	−0.0965
		(0.0760)	(0.0760)	(0.0448)	(0.1138)
σ		4.4683***	4.4942***	4.4858***	3.1524***
		(0.0537)	(0.0552)	(0.0541)	(0.0415)
l_1					0.4914***
					(0.0119)
r_1					0.8801***
					(0.0085)
m_1					0.0377
					(0.0345)
m_2					4.6819***
					(0.4596)
-LOGL		1.0083e+004	1.0079e+004	1.0079e+004	9.3987e+003
AIC		2.0170e+004	2.0163e+004	2.0162e+004	1.8809e+004
BIC		2.0182e+004	2.0175e+004	2.0174e+004	1.8846e+004
pm					0.9344
	Hansol Artone Paper Co Ltd	normal	TN	CN	CCN
μ		-0.0673	-0.0672	-0.0660	−0.1958***
		(0.0809)	(0.0808)	(0.1149)	(0.0416)
σ		3.1485***	3.1476***	3.1534***	1.3310***
		(0.0572)	(0.0572)	(0.0573)	(0.0368)
l_1					0.1582***
					(0.0057)
r_1					0.1749***
					(0.0062)
m_1					0.3571***
					(0.0285)
m_2					−0.3302***
					(0.0266)
-LOGL		3.8893e+003	3.8893e+003	3.8905e+003	3.5372e+003
AIC		7.7827e+003	7.7827e+003	7.7850e+003	7.0864e+003
BIC		7.7933e+003	7.7933e+003	7.7957e+003	7.1183e+003
pm					0.7632
	Iljin Electric Co Ltd	normal	TN	CN	CCN

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Table E.0.3 – continued from previous page

Moments/Parameters	Data	Four Models			
μ		0.0177	0.0183	0.0172	0.0519
		(0.0939)	(0.0939)	(0.0229)	(0.1192)
σ		3.5642***	3.5644***	3.5654***	2.8548***
		(0.0665)	(0.0665)	(0.0665)	(0.0549)
l_1					0.5392***
					(0.0224)
r_1					0.7814***
					(0.0270)
m_1					-0.1323
					(0.0905)
m_2					1.7726***
					(0.4487)
-LOGL		3.8729e+003	3.8729e+003	3.8732e+003	3.7040e+003
AIC		7.7499e+003	7.7497e+003	7.7505e+003	7.4199e+003
BIC		7.7604e+003	7.7603e+003	7.7610e+003	7.4516e+003
pm					0.9729
	Phoenix Holdings Inc.	normal	TN	CN	CCN
μ		-0.0114	-0.0110	−0.0111*	−0.0022
		(0.0680)	(0.0679)	(0.0070)	(0.0145)
σ		3.4989***	3.4993***	3.4996***	2.4352***
		(0.0481)	(0.0481)	(0.0481)	(0.0363)
l_1					0.3631***
					(0.0105)
r_1					0.8208***
					(0.0161)
m_1					0.2157***
					(0.0341)
m_2					4.1652***
					(0.5855)
-LOGL		7.0814e+003	7.0813e+003	7.0816e+003	6.5294e+003
AIC		1.4167e+004	1.4167e+004	1.4167e+004	1.3075e+004
BIC		1.4179e+004	1.4178e+004	1.4179e+004	1.3106e+004
pm					0.6785
5 French Stocks (daily limit of 10%)					
	Airbus Group (AIR.PA)	normal	TN	CN	CCN
μ		0.0399	0.0403	0.0409	0.1124***
		(0.0429)	(0.0429)	(0.2593)	(0.0386)
σ		2.4413***	2.4421***	2.4517***	2.1561***
		(.0303)	(0.0304)	(0.0306)	(0.0295)
l_1					0.4711***
					(0.0151)
r_1					0.8586***
					(0.0198)
m_1					0.4169***
					(0.0614)
m_2					3.6430***
					(0.9058)
-LOGL		7.4956e+003	7.4954e+003	7.5038e+003	7.3637e+003
AIC		1.4995e+004	1.4995e+004	1.5012e+004	1.4739e+004
BIC		1.5007e+004	1.5007e+004	1.5024e+004	1.4776e+004
pm					0.9682
	Essilor International SA (EI.PA)	normal	TN	CN	CCN
μ		0.0510	0.0510	0.0518*	−0.0647***
		(0.0348)	(0.0348)	(0.0237)	(0.0251)
σ		2.1021***	2.1019***	2.1405***	1.4684***
		(0.0246)	(0.0246)	(0.0260)	(0.0176)
l_1					0.7917***
					(0.0218)
r_1					0.5016***
					(0.0123)
m_1					−6.6412***
					(1.1616)
m_2					0.4348***
					(0.0887)
-LOGL		7.8989e+003	7.8989e+003	7.9560e+003	6.9852e+003

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Table E.0.3 – continued from previous page

Moments/Parameters	Data	Four Models			
AIC		1.5802e+004	1.5802e+004	1.5916e+004	1.3982e+004
BIC		1.5814e+004	1.5814e+004	1.5928e+004	1.4020e+004
pm					0.9709
	Bouygues SA (EN.PA)	normal	TN	CN	CCN
μ		-0.0082	-0.0081	-0.0067	−0.0246
		(0.0384)	(0.0384)	(0.0367)	(0.0234)
σ		2.3178***	2.3180***	2.3298***	1.5486***
		(0.0271)	(0.0272)	(0.0274)	(0.0080)
l_1					0.2568***
					(0.0086)
r_1					0.3347***
					(0.0155)
m_1					0.5563***
					(0.0303)
m_2					−0.4053***
					(0.0362)
-LOGL		8.2424e+003	8.2423e+003	8.2553e+003	7.9397e+003
AIC		1.6489e+004	1.6489e+004	1.6515e+004	1.5891e+004
BIC		1.6501e+004	1.6501e+004	1.6527e+004	1.5929e+004
pm					0.8470
	Carrefour SA (CA.PA)	normal	TN	CN	CCN
μ		-0.0215	-0.0215	−0.0217***	−0.1359***
		(0.0329)	(0.0329)	(0.0023)	(0.0520)
σ		1.9947***	1.9944***	1.9954***	1.0064**
		(0.0233)	(0.0233)	(0.0232)	(0.0510)
l_1					0.1247***
					(0.0062)
r_1					0.0735**
					(0.0290)
m_1					0.7096***
					(0.0264)
m_2					−0.6978***
					(0.0196)
-LOGL		7.7579e+003	7.7579e+003	7.7599e+003	7.4959e+003
AIC		1.5520e+004	1.5520e+004	1.5524e+004	1.5004e+004
BIC		1.5532e+004	1.5532e+004	1.5536e+004	1.5041e+004
pm					0.4911
	Renault Soci (RNO.PA)	normal	TN	CN	CCN
μ		0.0173	0.0179	0.0173	0.0502
		(0.0416)	(0.0416)	(0.0105)	(0.0392)
σ		2.5155***	2.5170***	2.5291***	1.7362***
		(0.0295)	(0.0283)	(0.0297)	(0.0339)
l_1					0.2919***
					(0.0089)
r_1					0.3091***
					(0.0102)
m_1					0.4752***
					(0.0295)
m_2					−0.5100***
					(0.0313)
-LOGL		8.5574e+003	8.5571e+003	8.5682e+003	8.3440e+003
AIC		1.7119e+004	1.7118e+004	1.7140e+004	1.6700e+004
BIC		1.7131e+004	1.7131e+004	1.7153e+004	1.6737e+004
pm					0.8202

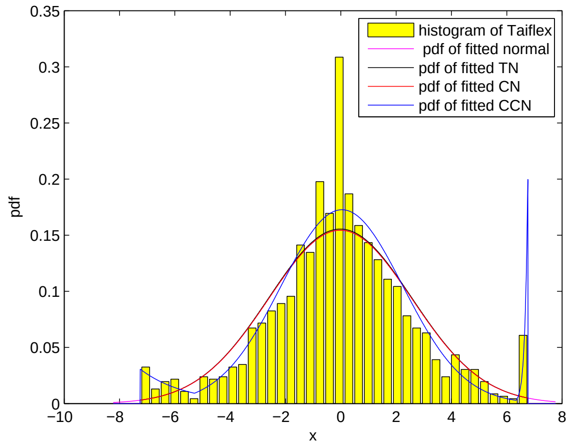
Notes: $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$

Table E.0.1: Data in Chapter 1

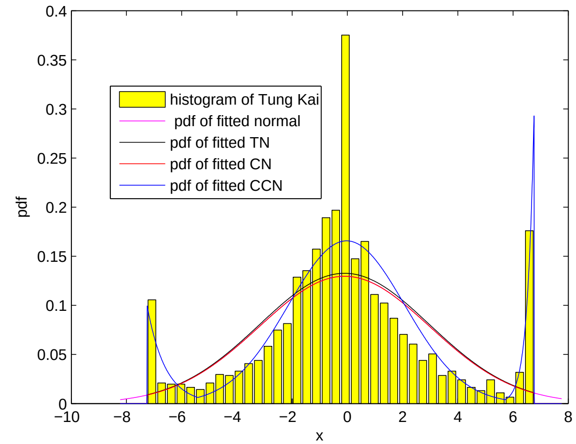
Taiwanese stocks	
TaiFlex	From September 1, 2008 to May 16, 2014
Tung Kai Technology	From August 20, 2002 to May 16, 2014
Tri Ocean Textile	From January 4, 2000 to June 21, 2014
Jye Tai Precision	From August 4, 2003 to May 16, 2014
Nan Kang Rubb Tire	From January 4, 2000 to May 16, 2014
Chinese stocks	
China MinSheng Bank	From December 19, 2000 to May 16, 2014
China Merchants Energy Shipping	From December 1, 2006 to May 16, 2014
Beijing North Star Company Limited	From October 16, 2006 to May 16, 2014
GD Power Development Company	From March 18, 2005 to May 16, 2014
Inner Mongolia Baotou Steel Union	From March 9, 2001 to May 16, 2014
Korean stocks	
Shin Woo Co., Ltd.	From January 4, 2000 to May 16, 2014
Borneo International Furniture BIF Co Ltd	From January 4, 2000 to May 16, 2014
Hansol Artone Paper Co Ltd	From December 28, 2007 to May 16, 2014
Iljin Electric Co Ltd	From August 1, 2008 to May 16, 2014
Phoenix Holdings Inc.	From August 4, 2003 to May 16, 2014
French stocks	
Airbus Group (AIR.PA)	From September 3, 2001 to May 16, 2014
Essilor International SA (EI.PA)	From January 3, 2000 to May 16, 2014
Bouygues SA (EN.PA)	From January 3, 2000 to May 16, 2014
Carrefour SA (CA.PA)	From January 3, 2000 to June 20, 2014
Renault Soci (RNO.PA)	From August 4, 2003 to May 16, 2014

Table E.0.2: Classification of the significance level of ΔBIC

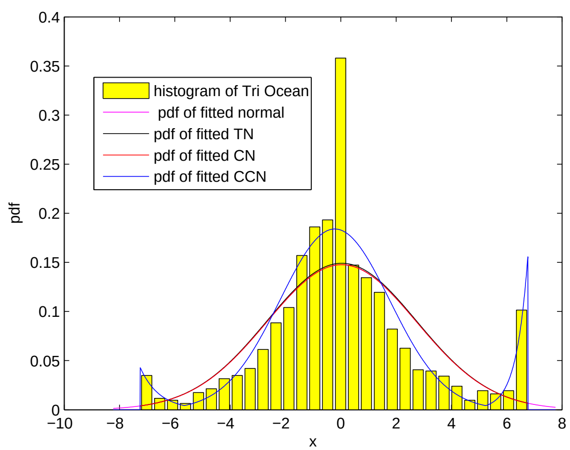
ΔBIC	**Evidence against higher BIC**
0 to 2	Not Worth more than a bare mention
2 to 6	Positive
6 to 10	Strong
> 10	Very Strong



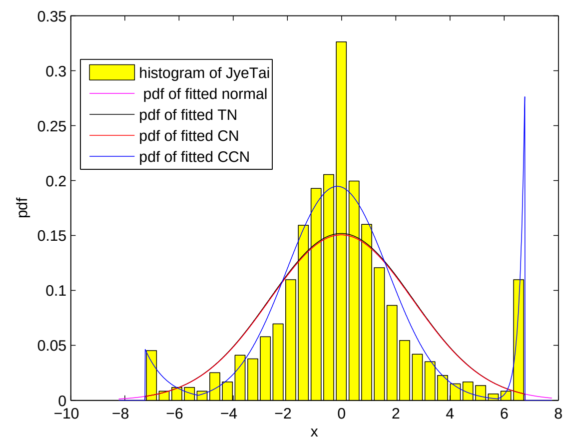
(a) *Taiflex*



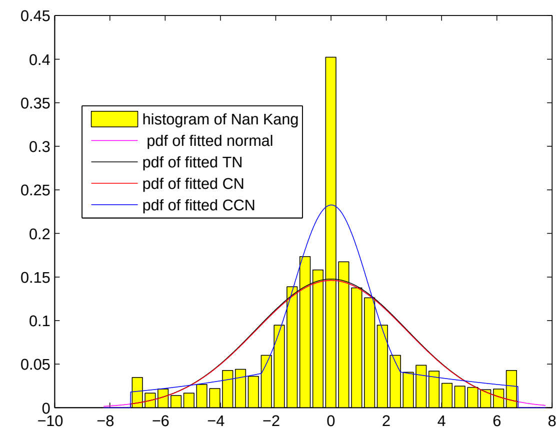
(b) *Tung Kai*



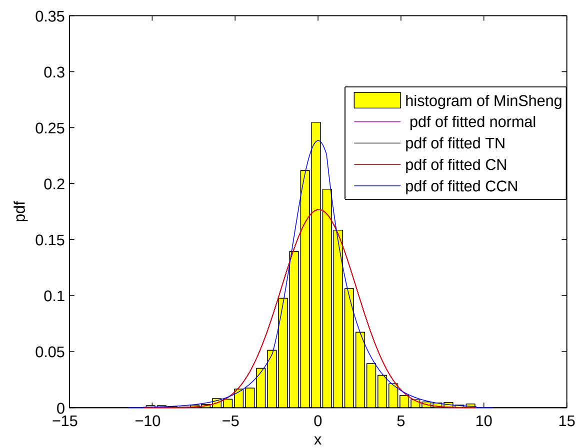
(c) *Tri Ocean*



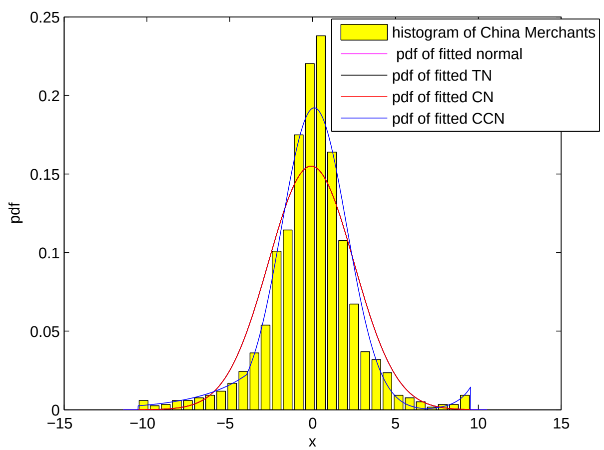
(d) *JyeTai*



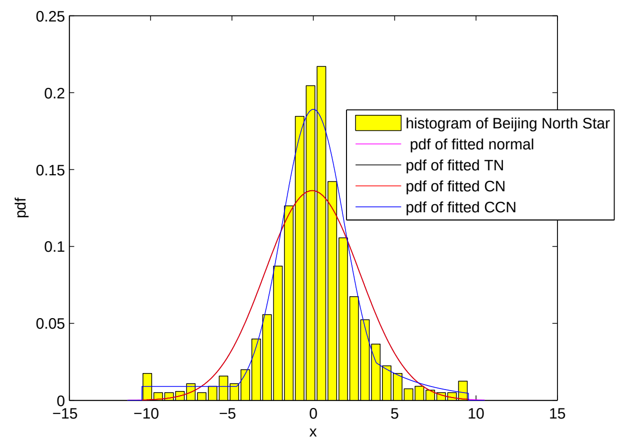
(a) *Nan Kang*



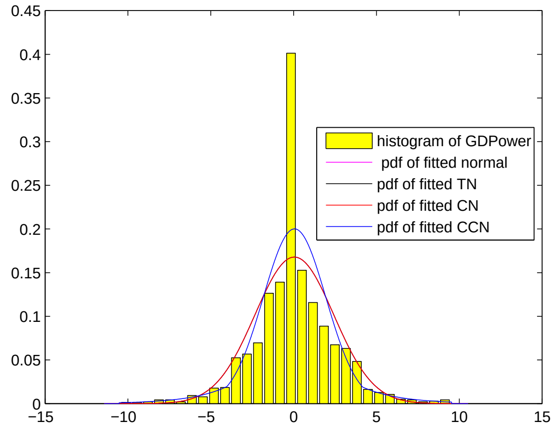
(b) *MinSheng*



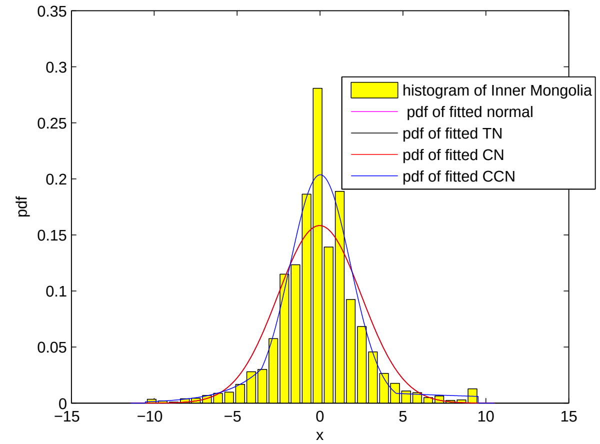
(c) *China Merchants Energy Shipping*



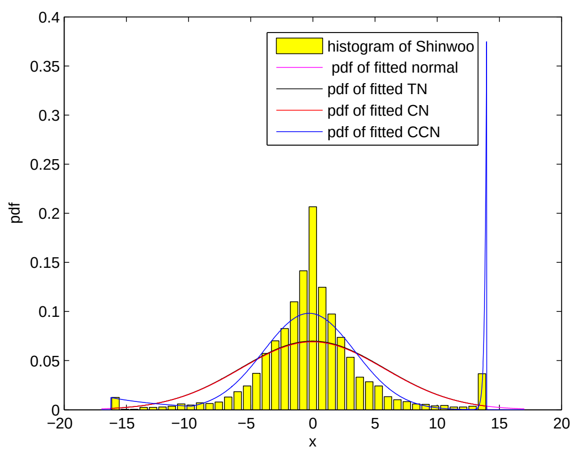
(d) *Beijing North Star*



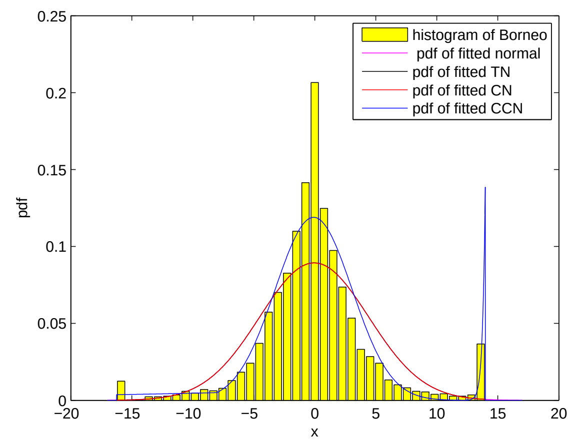
(a) *GD Power Development*



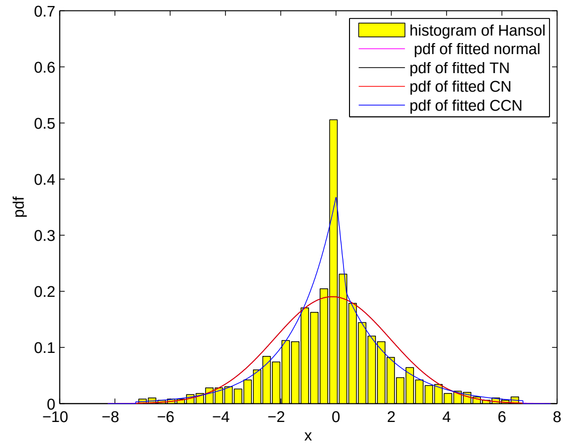
(b) *Inner Mongolia Baotou Steel Union*



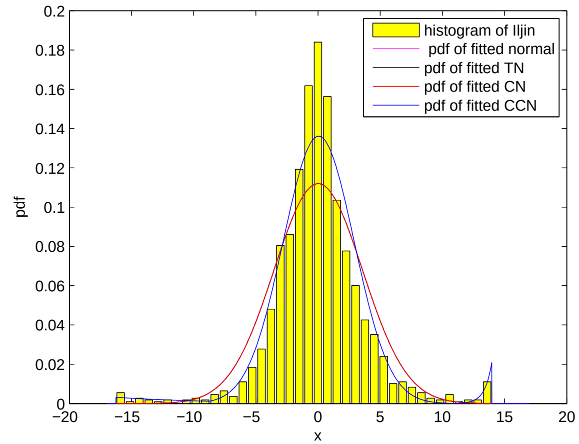
(c) *ShinWoo*



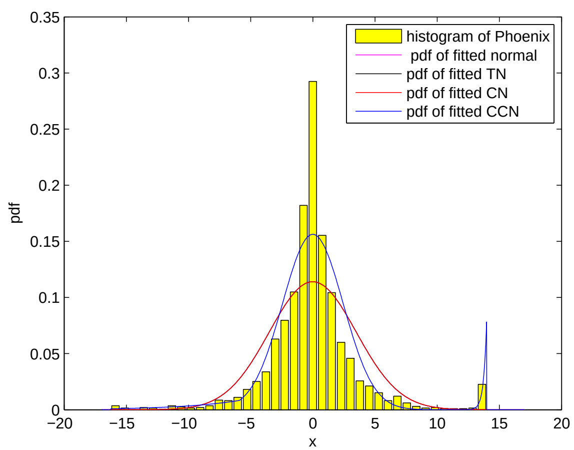
(d) *Borneo International Furniture*



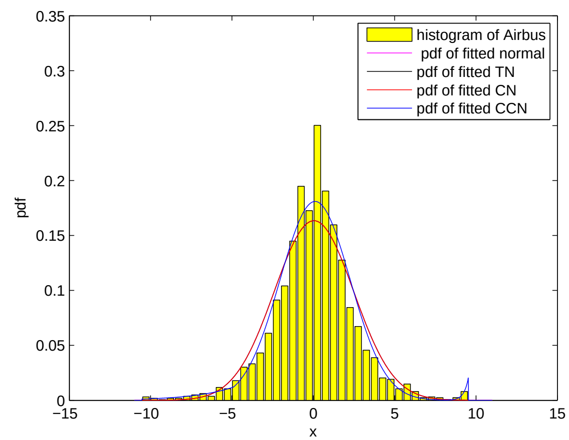
(a) *Hansol Artone Paper*



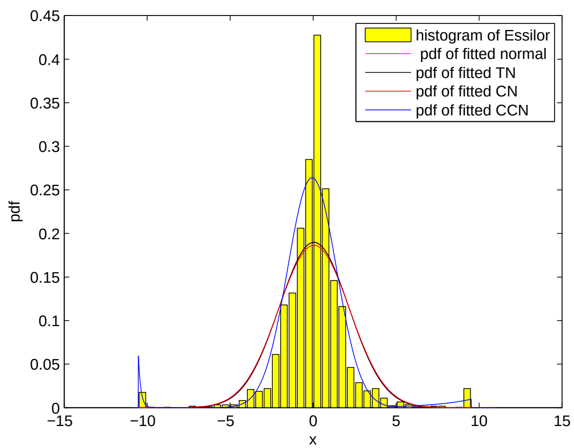
(b) *Iljin Electric Co Ltd*



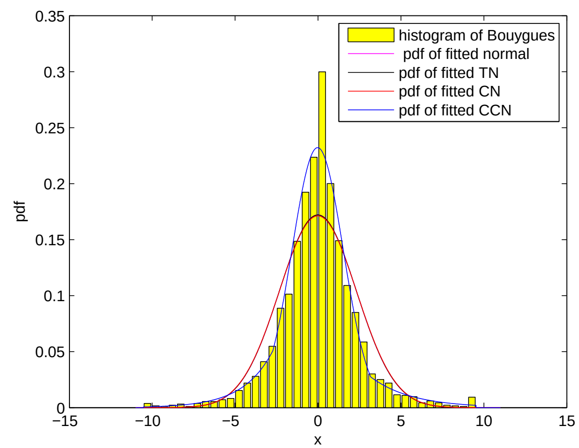
(c) *Phoenix*



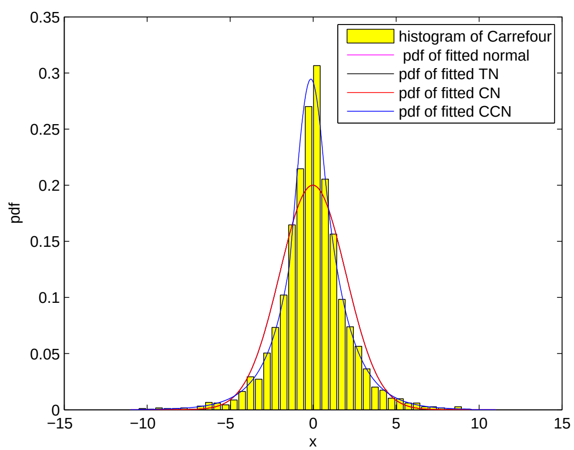
(d) *Airbus*



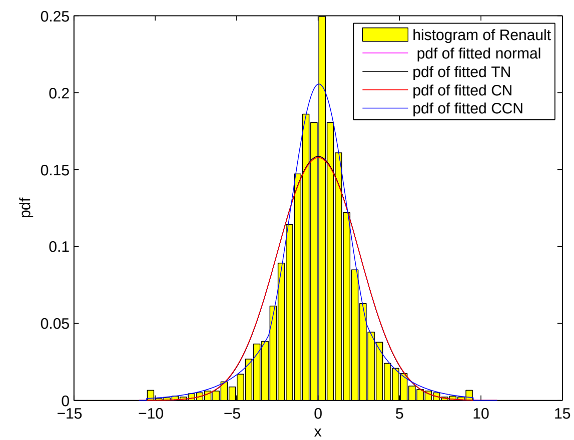
(a) *Essilor International*



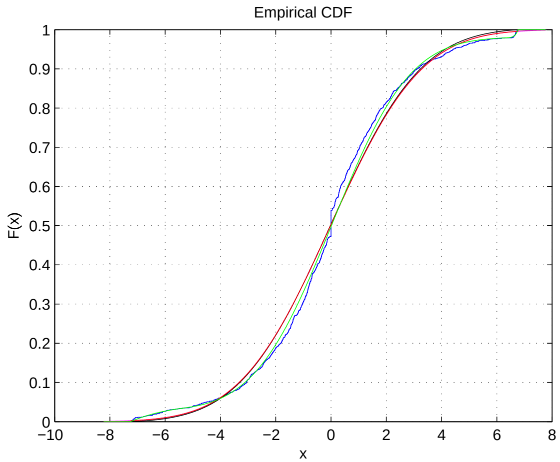
(b) *Bouygues SA (EN.PA)*



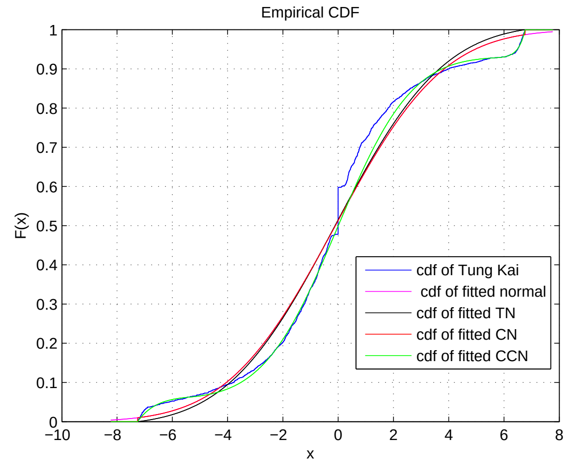
(c) *Carrefour SA (CA.PA)*



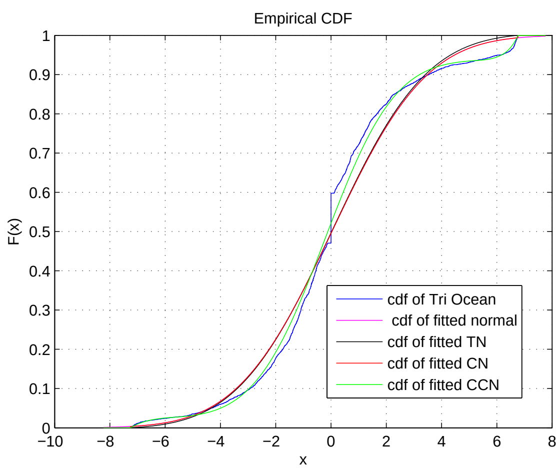
(d) *Renault Soci (CA.PA)*



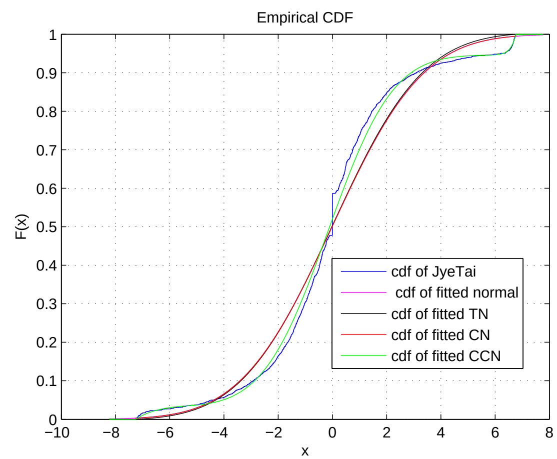
(a) *cdf of Taiflex*



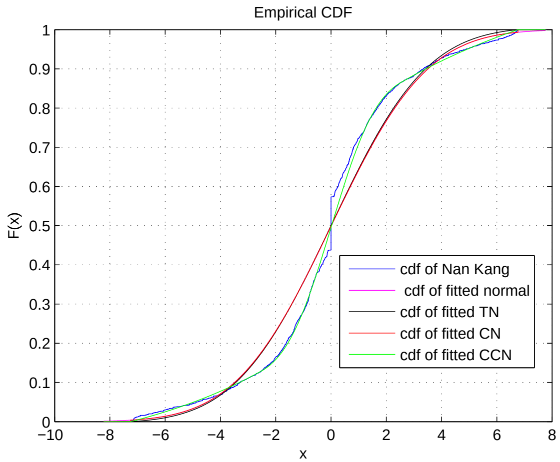
(b) *cdf of Tung Kai*



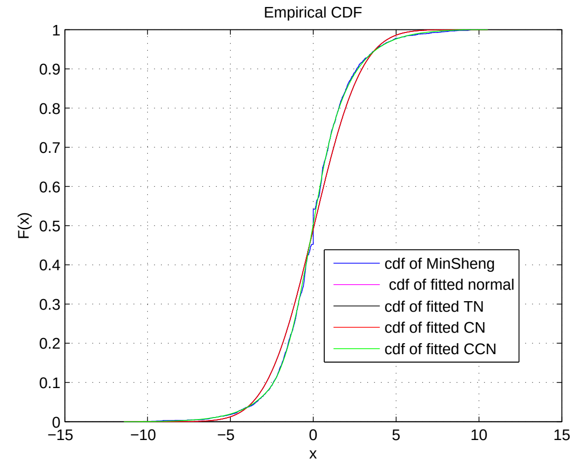
(c) *cdf of Tri Ocean*



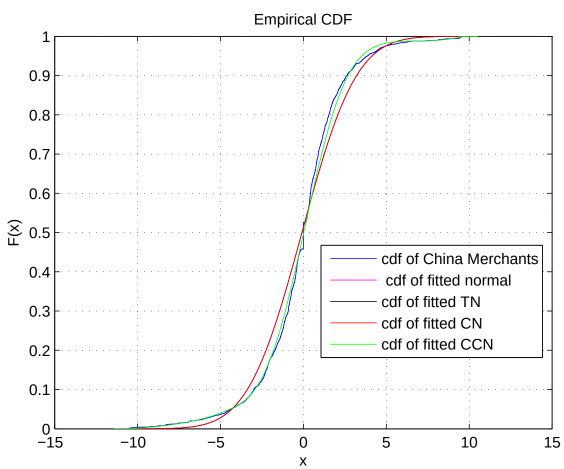
(d) *cdf of JyeTai*



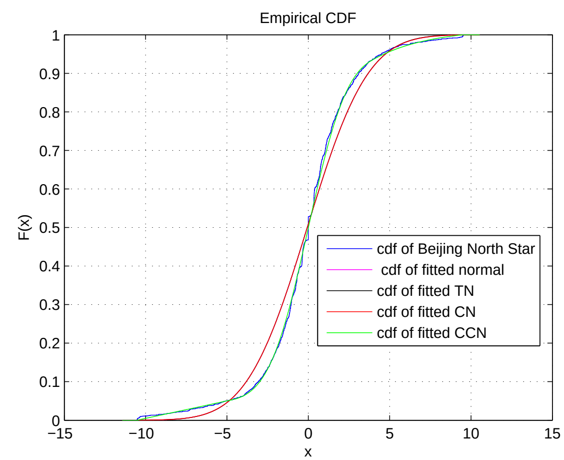
(a) *cdf of Nan Kang*



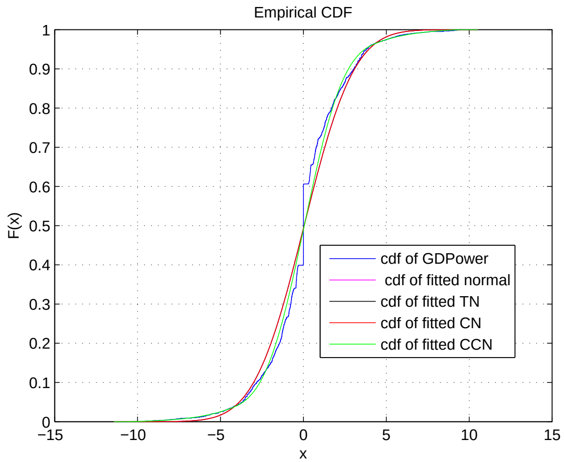
(b) *cdf of MinSheng*



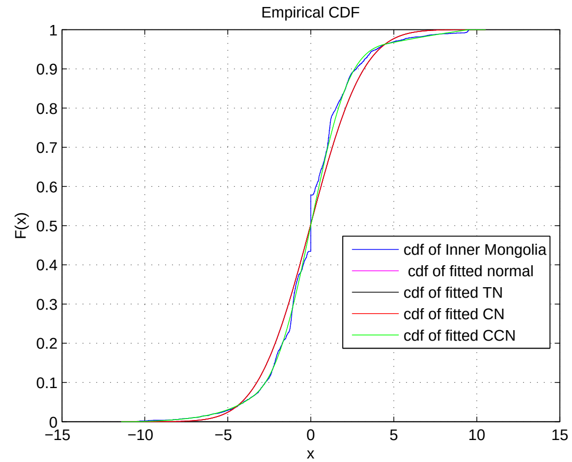
(c) *cdf of China Merchants*



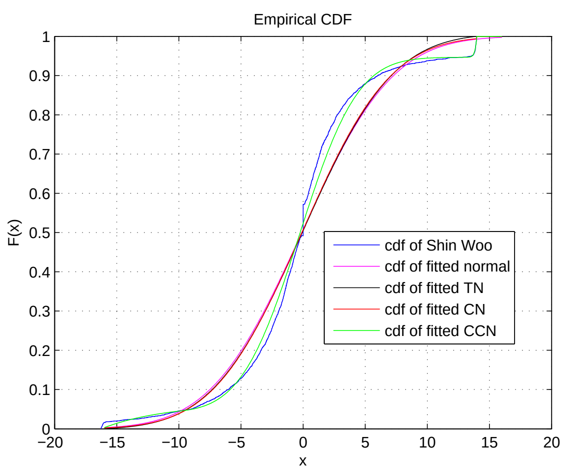
(d) *cdf of Beijing North Star*



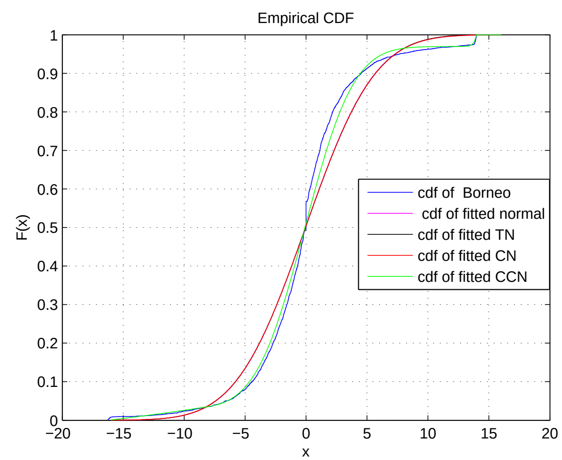
(a) *cdf of GD Power*



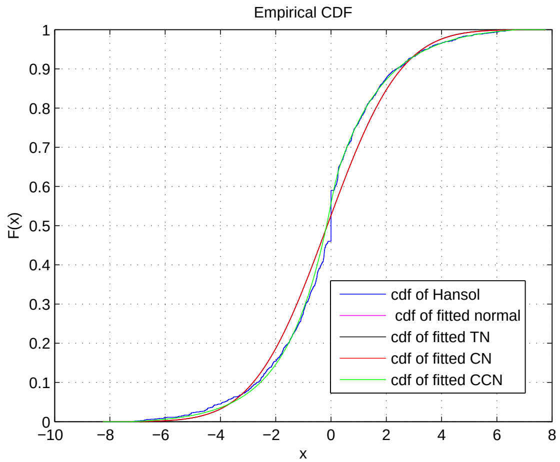
(b) *cdf of Inner Mongolia Baotou*



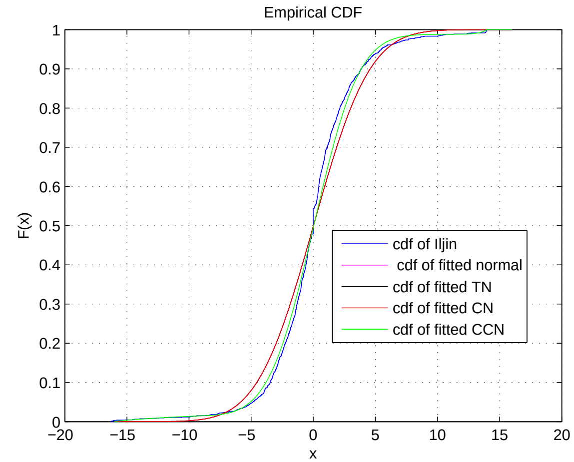
(c) *cdf of Shin Woo*



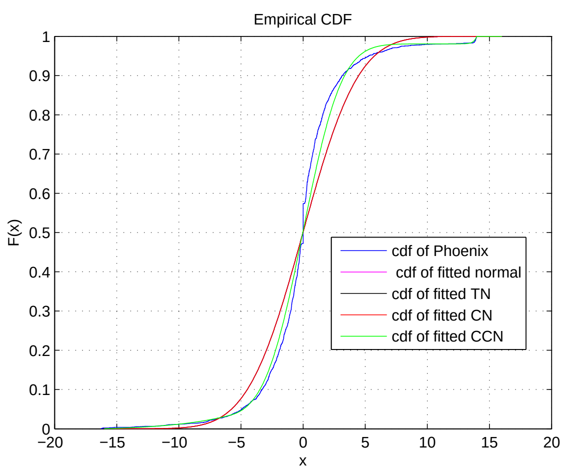
(d) *cdf of Borneo*



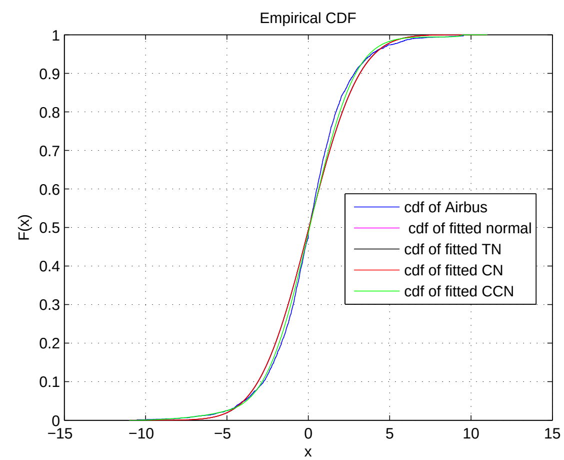
(a) *cdf of Hansol*



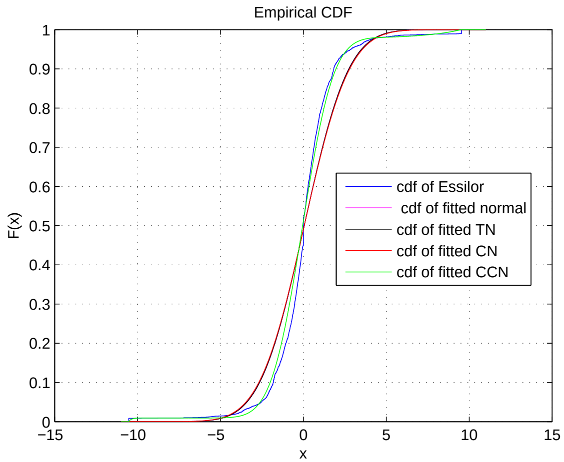
(b) *cdf of Iljin*



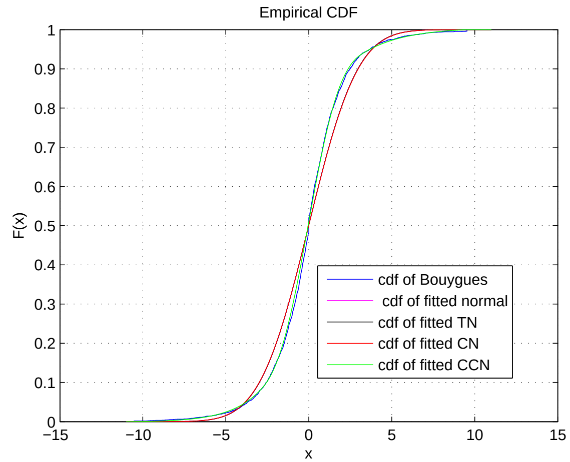
(c) *cdf of Phoenix*



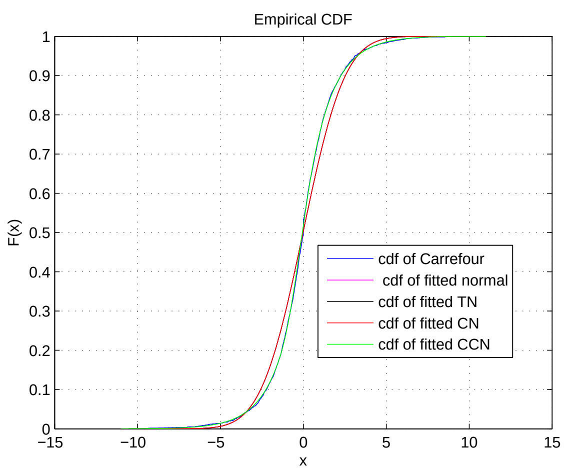
(d) *cdf of AirBus*



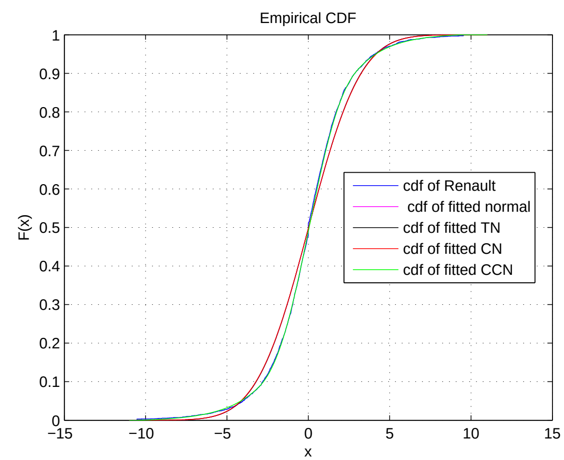
(a) *cdf of Essilor*



(b) *cdf of Bouygues*



(c) *cdf of Carrefour*



(d) *cdf of Renault*

Appendix F

Monte Carlo Simulations for GARCHTN, GARCHCN, and GARCHCCN

Table F.0.1: Monte Carlo simulation list: GARCH models

Experiment No.	True Model	Purpose	Data Size	Table	Rows
12	GARCHCN	Bounds change	5000	F.0.2	All
13	GARCHTN	Bounds change	5000	F.0.3	All
14	GARCHCCN	Bounds change	5000	F.0.4	1-5;6-10;11-15
15	GARCHCCN	m_1 and m_2 change	5000	F.0.4	6&11;7&12;8&13;9&14;1&15
17	GARCHCCN	l_1 and r_1 change	5000	F.0.4	1&6;2&7;3&8;4&9;5&10
18	GARCHCN	Bounds change	5000	F.0.2	All
19	GARCHTN	Bounds change	5000	F.0.3	All
20	GARCHCCN	Bounds change	5000	F.0.4	1-5;6-10;11-15
21	GARCHCCN	m_1 and m_2 change	5000	F.0.4	6&11;7&12;8&13;9&14;1&15
22	GARCHCCN	l_1 and r_1 change	5000	F.0.4	1&6;2&7;3&8;4&9;5&10

Table F.0.2: Results from Experiment 12 of GARCHCN

models	pm	bounds	κ	α	β	-LOGL
real value			0.15	0.8	0.07	
GARCHCN	0.9545	[-2,2]	0.1608**	0.7892***	0.0709***	7.2635e+003
			(0.0617/ 0.0616)	(0.0647/0.0643)	(0.0163/0.0154)	(61.3040)
GARCH			0.1599**	0.7891***	0.0482***	7.0362e+003
			(0.0811/0.3282)	(0.0872/0.3378)	(0.0108/0.0135)	(53.9886)
GARCHCN	0.9876	[-2.5,2.5]	0.1573***	0.7928***	0.0713***	7.3660e+003
			(0.0498/0.0469)	(0.0522/0.0496)	(0.0144/ 0.0135)	(71.8482)
GARCH			0.1570***	0.7962***	0.0598***	7.2793e+003
			(0.0482/0.0519)	(0.0508/ 0.0556)	(0.0115/ 0.0128)	(67.1229)
GARCHCN	0.9973	[-3,3]	0.1587***	0.7923***	0.0696***	7.3913e+003
			(0.0420/0.0458)	(0.0443/0.0481)	(0.0124/0.0127)	(63.3846)
GARCH			0.1589***	0.7944***	0.0648***	7.3633e+003
			(0.0412/0.0471)	(0.0436/ 0.0498)	(0.0115/ 0.0125)	(61.5284)
GARCHCN	0.9995	[-3.5,3.5]	0.1600***	0.7905***	0.0709***	7.4053e+003
			(0.0416/0.0418)	(0.0440/0.0442)	(0.0120/0.0126)	(73.7681)
GARCH			0.1602***	0.7913***	0.0690***	7.3973e+003
			(0.0413/ 0.0453)	(0.0435/ 0.0453)	(0.0114/0.0124)	(72.9906)
GARCHCN	0.9999	[-4,4]	0.1529***	0.7967***	0.0706***	7.4034e+003
			(0.0391/0.0404)	(0.0416/0.0430)	(0.0119/0.0125)	(73.7882)
GARCH			0.1531***	0.7969***	0.0701***	7.4013e+003
			(0.0392/ 0.0407)	(0.0416/ 0.0434)	(0.0118/0.0125)	(73.3713)
GARCHCN	1	[-5,5]	0.1547***	0.7961***	0.0699***	7.4081e+003
			(0.0393/0.0759)	(0.0423/0.0804)	(0.0122/0.0176)	(77.1545)
GARCH			0.1547***	0.7962***	0.0698***	7.4079e+003
			(0.0393/0.0751)	(0.0423/0.0792)	(0.0122/ 0.0173)	(77.0876)

Notes: $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$
Real mean=0, Real standard deviation=1.

Table F.0.4: Results from Experiments 14, 15, and 16 of GARCHCCN

Row No.	κ	α	β	l_1	r_1	m_1	m_2	**-LOGL**	**BIC**
bounds	[-3,3]								
	real value								
1	0.03	0.86	0.11	0.3	0.3	0.85	-0.85		
	GARCHCCN								
	0.1499***	0.8550***	0.0652***	0.6722*	0.6020	−7.6405***	−1.8945***	8.0937e+03	1.6247e+004
	(0.8283 / 0.1333)	(0.8341 / 0.0649)	(0.7207 / 0.0504)	(0.0240 / 0.3274)	(0.0274 / 0.3821)	(0.5505 / 16.4856)	(0.1734/ 1.6573)	(36.3695)	
	GARCH								
	0.1985***	0.8555***	0.0179***					8.2205e+03	1.6467e+004
	(0.1986 / 0.0979)	(0.1325 / 0.0664)	(0.0104/ 0.0089)					(46.0422)	
bounds	[-4,4]								
	real value								
2	0.03	0.86	0.11	0.3	0.3	0.85	-0.85		
	GARCHCCN								
	0.0509***	0.8857***	0.0715***	0.3988**	0.3747**	0.8289***	−0.8055***	8.9476e+03	1.7955e+004
	(0.0360 / 0.0466)	(0.0358 / 0.0326)	(0.0220 / 0.0357)	(0.0098 / 0.1313)	(0.0209 / 0.1473)	(0.0486 / 0.1005)	(0.0489/ 0.1129)	(38.0589)	
	GARCH								
	0.1511***	0.9119***	0.0187***					9.0315e+03	1.8089e+004
	(0.0862 / 0.0768)	(0.0441 / 0.0427)	(0.0074/ 0.0083)					(40.6363)	
bounds	[-5,5]								
	real value								

Continued on next page

Table F.0.4 – continued from previous page

Row No.	κ	α	β	l_1	r_1	m_1	m_2	-LOGL	BIC
3	0.03	0.86	0.11	0.3	0.3	0.85	-0.85		
	GARCHCCN								
	0.0725***	0.8537*** (0.0429 / 0.0838)	0.1051*** (0.0355 /0.0416)	0.3766* (0.0264 / 0.0522)	0.3699* (0.0181 / 0.1995)	0.3893 (0.0163 / 0.1864)	−3.0355 (0.7159 / 1.7617)	9.4949e+03 (5.4421/ 16.3927)	1.9049e+004 (65.9044)
	GARCH								
	0.2600*** (0.1150 / 0.0935)	0.8717*** (0.0481 / 0.0373)	0.0323*** (0.0091/ 0.0099)					9.5647e+003 (65.2999)	1.9155e+004
bounds	[-6,6]								
	real value								
4	0.03	0.86	0.11	0.3	0.3	0.85	-0.85		
	GARCHCCN								
	0.0431*** (0.0187 / 0.0421)	0.8578*** (0.0282 / 0.0254)	0.1087*** (0.0296 / 0.0260)	0.3279* (0.0254 / 0.1360)	0.3277** (0.0155 / 0.1167)	0.7991 (2.3060 / 9.2279)	−0.5339 (0.4800/ 4.4458)	9.7376e+03 (110.4976)	1.9535e+004
	GARCH								
	0.1743***	0.8988*** (0.1180 / 0.2105)	0.0449*** (0.0466 / 0.0688)	(0.0111/ 0.0110)				9.8458e+03	1.9717e+004 (99.4684)
bounds	[-7,7]								
	real value								
5	0.03	0.86	0.11	0.3	0.3	0.85	-0.85		
	GARCHCCN								
	0.0340*** (0.0093 / 0.0110)	0.8577*** (0.0148 / 0.0160)	0.1107*** (0.0155 / 0.0155)	0.3010*** (0.0107 / 0.0162)	0.3019*** (0.0101 / 0.0165)	0.8490 (3.0330 /7.0335)	−30.8489 (23.0335/ 100.0297)	9.6834e+03 (177.5358)	1.9426e+004
	GARCH								
	0.0848*** (0.0183 / 0.0418)	0.9061*** (0.0105 / 0.0171)	0.0702*** (0.0071/ 0.0136)					9.8436e+03 (165.1921)	1.9713e+004
bounds	[-3,3]								
	real value								
6		0.03	0.86	0.11	0.6	0.6	0.85	-0.85	
	GARCHCCN								
	0.0315*** (0.0076 / 0.0081)	0.8587*** (0.0168 / 0.0156)	0.1099*** (0.0154 / 0.0106)	0.6013*** (0.0183 / 0.0266)	0.6050*** (0.0176 / 0.0437)	0.8532*** (0.1144 / 0.1279)	−0.8014*** (0.1146/ 0.1263)	7.4489e+03 (112.5196)	1.4957e+004
	GARCH								
	0.0478*** (0.0102 / 0.0139)	0.8847*** (0.0141 / 0.0166)	0.0792*** (0.0092/ 0.0094)					7.5770e+03 (116.5319)	1.5180e+004
bounds	[-4,4]								
	real value								
7	0.03	0.86	0.11	0.6	0.6	0.85	-0.85		
	GARCHCCN								
	0.0309*** (0.0058 / 0.0057)	0.8591*** (0.0124 / 0.0128)	0.1096*** (0.0116 / 0.0118)	0.5965*** (0.0184 / 0.0286)	0.6003*** (0.0184 / 0.0275)	0.8361*** (0.1236 / 0.1472)	−0.8379*** (0.1265/ 0.1325)	7.5882e+03 (203.3828)	1.5236e+004
	GARCH								
	0.0300*** (0.0056 / 0.0066)	0.8738*** (0.0104 / 0.0124)	0.1094*** (0.0096/ 0.0103)					7.6695e+03 (209.5608)	1.5365e+004
bounds	[-5,5]								
	real values								
8	0.03	0.86	0.11	0.6	0.6	0.85	-0.85		
	GARCHCCN								
	0.0305*** (0.0051 / 0.0052)	0.8601*** (0.0118 / 0.0113)	0.1089*** (0.0105 / 0.0103)	0.6042*** (0.0241 / 0.0530)	0.6107*** (0.0257 / 0.0451)	12.3209 (0.1603 / 33.7560)	−0.8094*** (0.1846/ 0.2332)	7.1622e+03 (278.8020)	1.4384e+004
	GARCH								
	0.0256*** (0.0046 / 0.0048)	0.8649*** (0.0107 / 0.0114)	0.1178*** (0.0100/ 0.0097)					7.1985e+03 (285.6016)	1.4423e+004
bounds	[-6,6]								
	real value								
9	0.03	0.86	0.11	0.6	0.6	0.85	-0.85		
	GARCHCCN								
	0.0306*** (0.0052 / 0.0050)	0.8598*** (0.0120 / 0.0122)	0.1096*** (0.0122 / 0.0112)	0.6216*** (0.0360 / 0.0930)	0.6229*** (0.0432 / 0.0895)	125.7647 (136.5455 / 857.5000)	−6.4322 (20.7200/ 53.2233)	6.9088e+03 (255.0770)	1.3877e+004
	GARCH								
	0.0273*** (0.0049 / 0.0047)	0.8614*** (0.0116 / 0.0123)	0.1157*** (0.0101/ 0.0110)					6.9246e+03 (257.7580)	1.3875e+004
bounds	[-7,7]								
	real value								
10	0.03	0.86	0.11	0.6	0.6	0.85	-0.85		
	GARCHCCN								

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Table F.0.4 – continued from previous page

Row No.	κ	α	β	l_1	r_1	m_1	m_2	-LOGL	BIC
	0.0305*** (0.0060 / 0.0047)	0.8586*** (0.0133 / 0.0109)	0.1110*** (0.0115 / 0.0101)	0.6653*** (0.1949 / 0.1545)	0.6831*** (0.1841 / 0.1407)	156.5235 (491.9487 / 744.0744)	−62.8729 (500.0445/ 296.7431)	6.7619e+03 (212.1572)	1.3583e+004
	GARCH								
	0.0291*** (0.0052 / 0.0048)	0.8592*** (0.0124 / 0.0110)	0.1134*** (0.0102/ 0.0100)					6.7685e+03 (213.6784)	1.3563e+004
bounds	[-3,3]								
	real value								
11	0.03	0.86	0.11	0.6	0.6	0.55	-0.55		
	GARCHCCN								
	0.0313*** (0.0095 / 0.0104)	0.8579*** (0.0190 / 0.0188)	0.1123*** (0.0190 / 0.0166)	0.6032*** (0.0171 / 0.0325)	0.5994*** (0.0168 / 0.0324)	0.5282*** (0.1238 / 0.1252)	−0.5551*** (0.1083/0.1207)	7.8483e+03 (113.9027)	1.5756e+004
	GARCH								
	0.0619*** (0.0143 / 0.0206)	0.8858*** (0.0155 / 0.0170)	0.0746*** (0.0093/ 0.0101)					8.0362e+03 (122.5698)	1.6098e+004
bounds		[-4,4]							
	real value								
12	0.03	0.86	0.11	0.6	0.6	0.55	-0.55		
	GARCHCCN								
	0.0304*** (0.0059 / 0.0058)	0.8581*** (0.0119 / 0.0122)	0.1117*** (0.0118 / 0.0123)	0.6015*** (0.0161 / 0.0277)	0.5998*** (0.0162 / 0.0251)	0.5438*** (0.1013 / 0.1064)	−0.5500*** (0.1013/ 0.1112)	8.0918e+03 (201.8033)	1.6243e+004
	GARCH								
	0.0293*** (0.0057 / 0.0077)	0.8783*** (0.0095 / 0.0115)	0.1103*** (0.0093/ 0.0102)					8.2256e+03 (210.2005)	1.6477e+004
bounds	[-5,5]								
	real value								
13	0.03	0.86	0.11	0.6	0.6	0.55	-0.55		
	GARCHCCN								
	0.0302*** (0.0053 / 0.0047)	0.8595*** (0.0147 / 0.0100)	0.1105*** (0.0148 / 0.0098)	0.6014*** (0.0280 / 0.0336)	0.6050*** (0.0278 / 0.0312)	0.5505*** (0.1796 / 0.1609)	−0.5472*** (0.1970 / 0.1226)	7.6176e+03 (309.2230)	1.5295e+004
	GARCH								
	0.0226*** (0.0042 / 0.0042)	0.8673*** (0.0096 / 0.0105)	0.1234*** (0.0098/ 0.0097)					7.6882e+03 (318.6398)	1.5402e+004
bounds	[-6,6]								
	real value								
14	0.03	0.86	0.11	0.6	0.6	0.55	-0.55		
	GARCHCCN								
	0.0309*** (0.0051 / 0.0051)	0.8592*** (0.0118 / 0.0115)	0.1094*** (0.0104 / 0.0102)	0.6048*** (0.0303 / 0.0477)	0.6109*** (0.0356 / 0.0567)	0.5492* (0.2017 / 0.2248)	−4.8905 (28.6495 / 46.8255)	7.1159e+03 (291.7922)	1.4291e+004
	GARCH								
	0.0248*** (0.0044 / 0.0045)	0.8621*** (0.0107 / 0.0118)	0.1206*** (0.0100/ 0.0103)					7.1480e+03 (298.9383)	1.4322e+004
bounds	[-7,7]								
	real value								
15	0.03	0.86	0.11	0.6	0.6	0.55	-0.55		
	GARCHCCN								
	0.0306*** (0.0058 / 0.0055)	0.8595*** (0.0128 / 0.0124)	0.1099*** (0.0106 / 0.0110)	0.6417*** (0.0814 / 0.1102)	0.6542*** (0.0837 / 0.1277)	30.9309 (0.7174 / 252.6887)	−46.0195 (1.1695e+03/ 296.2876)	6.8839e+03 (258.7401)	1.3827e+004
	GARCH								
	0.0274*** (0.0046 / 0.0055)	0.8606*** (0.0110 / 0.0126)	0.1157*** (0.0101/ 0.0111)					6.8975e+03 (263.2629)	1.3821e+004

Notes: $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$

Table F.0.3: Results from Experiment 13 of GARCHTN

models	bounds	κ	α	beta	-LOGL
real value		0.15	0.8	0.03	
GARCHTN	[-2,2]	0.2198	0.7153**	0.0334	6.1141e+003
		(0.2094/0.1533)	(0.2524/ 0.1868)	(0.0208/ 0.0272)	(35.9863)
GARCH		0.3718	0.4582	0.0162	6.2280e+003
		(0.2656/0.0865)	(0.3727/ 0.0965)	(0.0114/ 0.0134)	(43.3077)
GARCHTN	[-2.5,2.5]	0.2185	0.7184***	0.0332*	6.5592e+003
		(0.1840/0.1287)	(0.2183/0.1543)	(0.0168/ 0.0189)	(50.2963)
GARCH		0.2739	0.6409**	0.0243*	6.5926e+003
		(0.2431/ 0.0490)	(0.2987/0.0531)	(0.0124/0.0126)	(53.5484)
GARCHTN	[-3,3]	0.2139	0.7258***	0.0309*	6.7159e+003
		(0.1956/ 0.0975)	(0.2240/ 0.1157)	(0.0131/ 0.0126)	(52.2444)
GARCH		0.2234	0.7138**	0.0273**	6.7229e+003
		(0.2105/ 0.0445)	(0.2430/ 0.0474)	(0.0120/0.0124)	(53.1007)
GARCHTN	[-3.5,3.5]	0.2367	0.7006***	0.0322**	6.7657e+003
		(0.2100/ 0.0401)	(0.2393/0.0427)	(0.0133/ 0.0125)	(56.6892)
GARCH		0.2430	0.6933**	0.0311**	6.7658e+003
		(0.2211/ 0.0410)	(0.2530/0.0436)	(0.0130/ 0.0123)	(56.7173)
GARCHTN	[-4,4]	0.2238	0.7967***	0.0706***	6.7710e+003
		(0.1920/ 0.0388)	(0.0416/0.0417)	(0.0119/0.0124)	(59.8072)
GARCH		0.2238	0.7133***	0.0314**	6.7722e+003
		(0.1920/ 0.0391)	(0.2212/0.0419)	(0.0128/ 0.0124)	(59.9601)
GARCHTN	[-5,5]	0.2430	0.6933**	0.0311**	6.7693e+003
		(0.2211/ 0.0438)	(0.2530/0.0468)	(0.0130/ 0.0132)	(59.6758)
GARCH		0.2245	0.7150***	0.0308**	6.7693e+003
		(0.1986/0.0439)	(0.2245/ 0.0468)	(0.0128/ 0.0131)	(59.6841)

Notes: $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$
Real mean=0, Real standard deviation=1.

Appendix G

GARCH simulations and Parameter Estimation - A comparison between 10,000 simulations with a data size of 500 and 1000 simulations with a data size of 500

Table G.0.1: GARCH Simulations and Parameters Estimated

models	κ	α	β
real value	0.15	0.8	0.05
GARCH	0.2622	0.6726**	0.0650
	(0.1846 / 0.2306)	(0.1959/ 0.2446)	(0.0481/0.0368)

10,000 simulations with a data size of 500.

models	κ	α	β
real value	0.15	0.8	0.05
GARCH	0.4105	0.5275	0.0582
	(5.9250 /0.3402)	(5.9783/0.3431)	(0.1372/0.0397)

1000 simulations with a data size of 500.

Notes: $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$

Table G.0.2: GARCH Simulations and Parameters Estimated as sample size changes

sample size	κ	α	β
real value	0.2	0.8	0.1
5000	0.2048***	0.7979***	0.0993***
	(0.0380)	(0.0271)	(0.0119)
1400	0.2305**	0.7848***	0.0993***
	(0.0951)	(0.0613)	(0.0243)
1000	0.2450	0.7725***	0.1033***
	(0.1311)	(0.0819)	(0.0256)

1000 simulations with a data size of 1000, 1400, or 5000.
Notes: $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$

Table G.0.3: GARCHCCN Simulations and Parameters Estimated as sample size changes

sample size	κ	α	β	l_1	r_1	m_1	m_2	$Lower$	$Upper$	$-LOGL$
real value	0.03	0.86	0.11	0.6	0.6	0.85	-0.85	-3	3	
5000	0.0315^{***}	0.8587^{***}	0.1099^{***}	0.6013^{***}	0.6050^{***}	0.8532^{***}	-0.8014^{***}			7.4489e+03
	(0.0076 / 0.0081)	(0.0168 / 0.0156)	(0.0154 / 0.0106)	(0.0183 / 0.0266)	(0.0176 / 0.0437)	(0.1144 / 0.1279)	(0.1146/ 0.1263)			(112.5196)
2200	0.0354^{**}	0.8526^{***}	0.1129^{***}	0.6020^{***}	0.6023^{***}	0.8344^{***}	-0.8124^{***}			3.2996e+03
	(0.0173/ 0.0159)	(0.0306/ 0.0301)	(0.0265 /0.0254)	(0.0296 / 0.0550)	(0.0302 / 0.0515)	(0.2095 / 0.2136)	(0.2043 / 0.1865)			(76.7135)
2000	0.0346^{**}	0.8515^{***}	0.1159^{***}	0.5967^{***}	0.5966^{***}	0.8163^{***}	-0.8231^{***}			3.0101e+03
	(0.0169/ 0.0170)	(0.0293/ 0.0305)	(0.0284 /0.0267)	(0.0296 / 0.0554)	(0.0285 / 0.0579)	(0.1944 / 0.2200)	(0.2005 /0.2522)			(64.7461)
1800	0.0320^{**}	0.8515^{***}	0.1160^{***}	0.5950^{***}	0.5995^{***}	0.8177^{***}	-0.7995^{***}			2.7049e+03
	(0.0231/ 0.0158)	(0.0363/ 0.0286)	(0.0312 / 0.0233)	(0.0309 / 0.0625)	(0.0306 / 0.0635)	(0.2494 / 0.2632)	(0.2385/0.2813)			(70.4308)
1600	0.0355^{*}	0.8496^{***}	0.1175^{***}	0.5998^{***}	0.6058^{***}	0.8159^{**}	-0.8142^{**}			2.4024e+03
	(0.0327 / 0.0168)	(0.0430/ 0.0307)	(0.0479 /0.0283)	(0.0370 / 0.0727)	(0.0404 / 0.0668)	(0.3750 / 0.2612)	(0.3122 / 0.2850)			(64.6101)
1400	2.2323	0.6972^{***}	0.1785	0.3102^{**}	0.3147^{**}	0.8312^{***}	-0.8450^{***}			2.2574e+03
	(93.1800/ 26.5765)	(2.7319/ 0.2729)	(1.3632 /0.2017)	(0.1658 / 0.1222)	(0.6221 / 0.1250)	(0.3326 / 0.1079)	(0.4692 / 0.1094)			(22.8479)

1000 simulations with a data size of 1400, 1600, 1800, 2000, 2200, or 5000.
Notes: $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$

Appendix H

Fitted GARCH, GARCHTN, GARCHCN, and GARCHCCN of 5 Taiwanese, 5 Chinese, 5 Korean, and 5 French stocks; and out-of-sample VaR test statistics

Table H.0.1: Out-of-sample VaR test statistics

Data	p/model	x/T	Kupiec LR test	$E(shortfall^2)$	LR_{cc}
Acer	0.1				
	GARCH	0.0680	6.3372(0.025)	2.0223	9.1482(0.025)
	GARCHTN	0.0775	2.4198	1.6928	5.2573 (0.1)
	GARCHCN	0.0775	2.4198	1.9041	5.2573(0.1)
	GARCHCCN	0.1128	0.0950	1.8641	1.9358
	0.05				
	GARCH	0.0340	3.0215	1.6982	5.3947 (0.1)
	GARCHTN	0.0350	2.1073	0.7164	2.5510
	GARCHCN	0.0350	2.1073	0.8296	5.0622(0.1)
	GARCHCCN	0.0498	0.0425	0.7737	2.2192
	0.025				
	GARCH	0.0180	1.1120	1.3809	3.2385
	GARCHTN	0.0150	1.9110	0.3423	5.2002(0.1)
	GARCHCN	0.0175	1.0296	0.3881	3.7054
	GARCHCCN	0.0200	0.4399	0.2314	2.6094
ChinaTrust	0.1				
	GARCH	0.0675	5.2396 (0.025)	0.7330	5.7440(0.1)
	GARCHTN	0.0700	4.4218(0.05)	0.7091	5.0741 (0.1)
	GARCHCN	0.0700	4.4218(0.05)	0.7091	5.0741 (0.1)
	GARCHCCN	0.0775	2.4198	0.6413	2.5801
	0.05				
	GARCH	0.0250	6.3979 (0.025)	0.3054	6.9121(0.05)
	GARCHTN	0.0275	5.0591(0.025)	0.2993	5.6829(0.1)
	GARCHCN	0.0275	5.0591(0.025)	0.2993	5.6829(0.1)
	GARCHCCN	0.0225	7.9423(0.005)	0.2539	8.3577(0.025)
	0.025				
	GARCH	0.0200	0.4399	0.1362	0.7673
	GARCHTN	0.0150	1.9110	0.1432	2.0942
	GARCHCN	0.0150	1.9110	0.1432	2.0942
	GARCHCCN	0.0125	3.1324(0.1)	0.0992	3.2593
Clevo	0.1				
	GARCH	0.0400	20.2443(0.005)	3.5480	21.5815(0.005)
	GARCHTN	0.0375	22.2724 (0.005)	3.4039	23.4446 (0.005)
	GARCHCN	0.0400	20.2443(0.005)	3.5446	21.5815(0.005)

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Table H.0.1 – continued from previous page

Data	p	x/T	Kupiec LR test	$E(shortfall^2)$	LR_{cc}
	GARCHCCN	0.0525	11.9226(0.005)	2.9662	14.2571 (0.005)
	0.05				
	GARCH	0.0250	6.3979 (0.01)	2.1705	6.9121(0.05)
	GARCHTN	0.0200	9.7144(0.005)	2.1055	10.0418(0.01)
	GARCHCN	0.0250	6.3979(0.01)	2.1714	6.9121(0.05)
	GARCHCCN	0.0275	5.0591(0.025)	1.7856	5.6829 (0.1)
	0.025				
	GARCH	0.0125	3.1324(0.1)	1.4619	3.2593
	GARCHTN	0.0125	3.1324(0.1)	1.3872	3.2593
	GARCHCN	0.0125	3.1324 (0.1)	1.4644	3.2593
	GARCHCCN	0.0150	1.9110	1.1739	2.0942
Fubon	0.1				
	GARCH	0.0600	8.1812(0.005)	1.5236	8.3520(0.025)
	GARCHTN	0.0600	8.1812(0.005)	1.5021	8.3520 (0.025)
	GARCHCN	0.0600	8.1812(0.005)	1.5140	8.3520 (0.025)
	GARCHCCN	0.0700	4.4218(0.05)	1.4806	5.0741 (0.1)
	0.05				
	GARCH	0.0400	0.9014	0.7348	1.0893
	GARCHTN	0.0400	0.9014	0.7234	1.0893
	GARCHCN	0.0400	0.9014	0.7289	1.0893
	GARCHCCN	0.0425	0.4980	0.7286	0.6013
	0.025				
	GARCH	0.0225	0.1061	0.3687	0.5215
	GARCHTN	0.0250	0	0.3632	0.5142
	GARCHCN	0.0225	0.1061	0.3653	0.5215
	GARCHCCN	0.0225	0.1061	0.3521	0.5215
Formosa Petrochemical Corp	0.1				
	GARCH	0.0600	8.1812 (0.005)	1.5236	8.3520(0.025)
	GARCHTN	0.0600	8.1812(0.005)	1.5021	8.3520(0.025)
	GARCHCN	0.0600	8.1812 (0.005)	1.5140	8.3520(0.025)
	GARCHCCN	0.1150	0.9587	0.9319	2.5319
	0.05				
	GARCH	0.0400	0.9014	0.7348	1.0893
	GARCHTN	0.0400	0.9014	0.7234	1.0893
	GARCHCN	0.0400	0.9014	0.7292	1.0893
	GARCHCCN	0.0525	0.0518	0.3862	0.7185
	0.025				
	GARCH	0.0225	0.1061	0.3687	0.5215
	GARCHTN	0.0250	0	0.3632	0.5142
	GARCHCN	0.0225	0.1061	0.3656	0.5215
	GARCHCCN	0.0350	1.4624	0.1269	1.9060
TsingHuaTongFang	0.1				
	GARCH	0.0675	5.2396(0.025)	4.2827	5.7440(0.1)
	GARCHTN	0.0675	5.2396(0.025)	4.1993	5.7440(0.1)
	GARCHCN	0.0675	5.2396(0.025)	4.2459	5.7440(0.1)
	GARCHCCN	0.0950	0.1128	3.8328	0.7014
	0.05				
	GARCH	0.0450	0.2175	3.0584	0.2622
	GARCHTN	0.0450	0.2175	1.9895	0.2622
	GARCHCN	0.0450	0.2175	2.0055	0.2622
	GARCHCCN	0.0475	0.0535	1.6812	0.0642
	0.025				
	GARCH	0.0300	0.3860	2.1427	1.1303
	GARCHTN	0.0300	0.3860	0.9312	1.1303
	GARCHCN	0.0300	0.3860	0.9250	1.1303
	GARCHCCN	0.0250	0	0.5946	0.5142
GDPower	0.1				
	GARCH	0.0350	24.4391(0.005)	0.9913	24.8828(0.005)
	GARCHTN	0.0350	24.4391(0.005)	0.9913	24.8828(0.005)
	GARCHCN	0.0325	26.7540(0.005)	1.1256	27.3738 (0.005)
	GARCHCCN	0.0600	8.1812(0.005)	0.9872	8.3520(0.025)
	0.05				
	GARCH	0.0400	0.9014	1.0360	2.1533
	GARCHTN	0.0200	9.7144 (0.005)	0.3381	10.0418(0.01)
	GARCHCN	0.0175	11.7422 (0.005)	0.4031	11.9923(0.005)
	GARCHCCN	0.0225	7.9423(0.01)	0.3262	9.6879(0.01)
	0.025				
	GARCH	0.0075	6.9011 (0.01)	0.4510	6.9465(0.05)
	GARCHTN	0.0075	6.9011(0.01)	0.0939	6.9465(0.05)
	GARCHCN	0.0100	4.7615(0.05)	0.1139	4.8425(0.1)
	GARCHCCN	0.0100	4.7615(0.05)	0.0169	4.8425(0.1)
Inner Mongolia Baotou	0.1				
	GARCH	0.0875	0.7219	4.6064	7.4631 (0.05)
	GARCHTN	0.0875	0.7219	4.4557	7.4631(0.05)
	GARCHCN	0.0900	0.4583	4.5613	7.6106(0.05)
	GARCHCCN	0.1125	0.6702	4.6614	6.4300 (0.025)
	0.05				
	GARCH	0.0475	0.0535	2.4426	1.9543
	GARCHTN	0.0500	0	2.3465	2.1118

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Table H.0.1 – continued from previous page

Data	p	x/T	Kupiec LR test	$E(shortfall^2)$	LR_{cc}
	GARCHCN	0.0500	0	2.4607	2.1118
	GARCHCCN	0.0525	0.0518	2.2424	2.3864
	0.025				
	GARCH	0.0300	0.3860	1.3663	1.1303
	GARCHTN	0.0275	0.0994	1.3100	0.7232
	GARCHCN	0.0275	0.0994	1.4039	0.7232
	GARCHCCN	0.0250	0	0.9304	0.5142
China Merchants Bank	0.1				
	GARCH	0.0800	1.8953	3.6613	3.3142
	GARCHTN	0.0800	1.8953	3.6148	3.3142
	GARCHCN	0.0825	1.4387	3.5119	3.0921
	GARCHCCN	0.0900	0.4583	4.5417	1.1135
	0.05				
	GARCH	0.0400	0.9014	2.4313	2.2386
	GARCHTN	0.0425	0.4980	2.4063	2.0116
	GARCHCN	0.0425	0.4980	2.3789	2.0116
	GARCHCCN	0.0575	0.4528	2.9483	0.5504
	0.025				
	GARCH	0.0250	0	1.8758	0.5142
	GARCHTN	0.0250	0	1.8426	0.5142
	GARCHCN	0.0250	0	1.8445	0.5142
	GARCHCCN	0.0250	0	2.1296	0.5142
ShangHai International Airport	0.1				
	GARCH	0.0550	10.5805(0.005)	1.1631	10.6248(0.005)
	GARCHTN	0.0525	11.9226(0.005)	1.2123	11.9341 (0.005)
	GARCHCN	0.0425	18.3465(0.005)	1.3009	18.4498(0.005)
	GARCHCCN	0.0950	0.1128	1.0812	0.1605
	0.05				
	GARCH	0.0275	5.0591 (0.025)	1.1555	5.6829 (0.1)
	GARCHTN	0.0275	5.0591(0.025)	1.0296	5.6829 (0.1)
	GARCHCN	0.0250	6.3979 (0.025)	0.6278	6.9121 (0.05)
	GARCHCCN	0.0400	0.9014	0.5409	2.2386
	0.025				
	GARCH	0.0175	1.0296	0.9899	1.2796
	GARCHTN	0.0175	0.6017	0.3285	1.2796
	GARCHCN	0.0075	6.9011 (0.01)	0.3565	6.9465(0.05)
	GARCHCCN	0.0175	1.0296	0.2643	1.2796
Naver	0.1				
	GARCH	0.0700	4.4218(0.05)	5.4578	5.0741(0.1)
	GARCHTN	0.0700	4.4218(0.05)	5.4143	5.0741 (0.1)
	GARCHCN	0.0700	4.4218(0.05)	5.4071	5.0741 (0.1)
	GARCHCCN	0.0800	1.8953	5.3770	1.9781
	0.05				
	GARCH	0.0475	0.0535	2.9125	1.9543
	GARCHTN	0.0450	0.2175	2.8852	1.9189
	GARCHCN	0.0450	0.2175	2.8840	1.9189
	GARCHCCN	0.0525	0.0518	2.9241	0.0633
	0.025				
	GARCH	0.0300	0.3860	1.6339	1.1303
	GARCHTN	0.0300	0.3860	1.6149	1.1303
	GARCHCN	0.0300	0.3860	1.6139	1.1303
	GARCHCCN	0.0325	0.8446	1.6058	1.7204
Samsung	0.1				
	GARCH	0.0825	1.4387	2.8169	2.0683
	GARCHTN	0.0800	1.8953	2.9594	2.7264
	GARCHCN	0.0825	1.4387	2.7738	2.0683
	GARCHCCN	0.0875	0.7219	2.8120	1.0360
	0.05				
	GARCH	0.0550	0.2042	1.7381	0.6924
	GARCHTN	0.0525	0.0518	1.8551	0.0633
	GARCHCN	0.0525	0.0518	1.7070	0.0633
	GARCHCCN	0.0525	0.0518	1.7072	0.0633
	0.025				
	GARCH	0.0175	1.0296	1.2249	1.2796
	GARCHTN	0.0175	1.0296	1.3223	1.2796
	GARCHCN	0.0175	1.0296	1.1987	1.2796
	GARCHCCN	0.0175	1.0296	1.1671	1.2796
Willbes	0.1				
	GARCH	0.0650	6.1368	6.1752	6.1969(0.05)
	GARCHTN	0.0650	6.1368	5.9573	6.1969 (0.05)
	GARCHCN	0.0650	6.1368	6.1752	6.1969 (0.05)
	GARCHCCN	0.1075	0.2446	5.5633	1.6030
	0.05				
	GARCH	0.0375	1.4350	3.4444	1.7357
	GARCHTN	0.0375	1.4350	3.2820	1.7357
	GARCHCN	0.0375	1.4350	3.4444	1.7357
	GARCHCCN	0.0525	0.0518	2.2954	0.7185
	0.025				
	GARCH	0.0150	1.9110	2.2578	5.2002(0.1)

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Table H.0.1 – continued from previous page

Data	p	x/T	Kupiec LR test	$E(shortfall^2)$	LR_{cc}
	GARCHTN	0.0125	3.1324	2.1282	7.1809(0.05)
	GARCHCN	0.0150	1.9110	2.2578	5.2002(0.1)
	GARCHCCN	0.0200	0.4399	0.7911	0.7673
Enex	0.1				
	GARCH	0.0550	10.5805(0.01)	6.1020	13.0295(0.05)
	GARCHTN	0.0550	10.5805 (0.01)	6.0077	13.0295 (0.005)
	GARCHCN	0.0550	10.5805(0.01)	6.0301	13.0295 (0.005)
	GARCHCCN	0.1000	0	5.4330	0.2790
	0.05				
	GARCH	0.0250	6.3979(0.01)	3.1907	6.9121(0.025)
	GARCHTN	0.0350	6.3979 (0.01)	3.1420	6.9121 (0.025)
	GARCHCN	0.0250	6.3979 (0.01)	3.1467	6.9121 (0.025)
	GARCHCCN	0.0350	2.1073	2.2367	3.1258
	0.025				
	GARCH	0.0150	1.9110	1.8082	2.0942
	GARCHTN	0.0150	1.9110	1.7755	2.0942
	GARCHCN	0.0150	1.9110	1.7712	2.0942
	GARCHCCN	0.0150	1.9110	0.9629	2.0942
Posco	0.1				
	GARCH	0.0675	5.2396 (0.025)	1.2108	5.7440(0.1)
	GARCHTN	0.0750	3.0143 (0.1)	1.4139	3.2786
	GARCHCN	0.0800	1.8953	2.6186	6.0881 (0.05)
	GARCHCCN	0.0700	4.4218 (0.05)	1.0427	5.0741(0.1)
	0.05				
	GARCH	0.0425	0.4980	0.7353	2.0116
	GARCHTN	0.0375	1.4350	0.7735	1.7357
	GARCHCN	0.0350	2.1073	1.4712	8.9590(0.025)
	GARCHCCN	0.0425	0.4980	0.5947	2.0116
	0.025				
	GARCH	0.0200	0.4399	0.5204	0.7673
	GARCHTN	0.0300	0.3860	0.4427	1.2187
	GARCHCN	0.0250	0	0.8816	1.3886
	GARCHCCN	0.0175	1.0296	0.4018	1.2796
French Stocks					
BNP	0.1				
	GARCH	0.0775	2.4198	1.7252	2.5801
	GARCHTN	0.0725	3.6809(0.1)	1.7958	3.6874
	GARCHCN	0.0775	2.4198	1.7439	2.5801
	GARCHCCN	0.0825	1.4387	1.6832	1.4698
	0.05				
	GARCH	0.0450	0.2175	0.7955	1.9189
	GARCHTN	0.0475	0.0535	0.8155	1.9543
	GARCHCN	0.0500	0	0.8083	2.1118
	GARCHCCN	0.0500	0	0.7728	2.1118
	0.025				
	GARCH	0.0325	0.8446	0.3406	1.7204
	GARCHTN	0.0325	0.8446	0.3455	1.7204
	GARCHCN	0.0325	0.8446	0.3483	1.7204
	GARCHCCN	0.0325	0.8446	0.3176	1.7204
Danone	0.1				
	GARCH	0.0725	3.6809(0.1)	0.8220	3.6816
	GARCHTN	0.0725	3.6809(0.1)	0.3772	3.6816
	GARCHCN	0.0725	3.6809(0.1)	0.8017	3.6816
	GARCHCCN	0.0875	0.7219	0.8703	0.7221
	0.05				
	GARCH	0.0500	0	0.3777	2.0035
	GARCHTN	0.0475	0.0535	0.8212	1.8518
	GARCHCN	0.0450	0.2175	0.3694	1.8223
	GARCHCCN	0.0600	0.7937	0.4252	3.7357
	0.025				
	GARCH	0.0250	0	0.1952	0.4622
	GARCHTN	0.0250	0	0.1948	0.4622
	GARCHCN	0.0250	0	0.1899	0.4622
	GARCHCCN	0.0325	0.8446	0.2166	1.6520
Gemalto	0.1				
	GARCH	0.0600	8.1812 (0.005)	1.4286	8.3520(0.025)
	GARCHTN	0.0600	8.1812(0.005)	1.4261	8.3520(0.025)
	GARCHCN	0.0600	8.1812(0.005)	1.4230	8.3520(0.025)
	GARCHCCN	0.0775	2.4198	1.9764	2.5055
	0.05				
	GARCH	0.0300	3.9074 (0.05)	0.4844	4.6517 (0.1)
	GARCHTN	0.0300	3.9074(0.05)	0.4835	4.6517(0.1)
	GARCHCN	0.0275	5.0591 (0.025)	0.4802	5.6829(0.1)
	GARCHCCN	0.0500	0	0.8641	0.0000
	0.025				
	GARCH	0.0200	0.4399	0.1229	0.7673
	GARCHTN	0.0200	0.4399	0.1231	0.7673
	GARCHCN	0.0200	0.4399	0.1198	0.7673
	GARCHCCN	0.0275	0.0994	0.3377	0.7232

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Table H.0.1 – continued from previous page

Data	p	x/T	Kupiec LR test	$E(shortfall^2)$	LR_{cc}
Vallourec	0.1				
	GARCH	0.0725	3.6809 (0.1)	2.1780	3.6874
	GARCHTN	0.0750	3.0143 (0.1)	2.0923	3.0493
	GARCHCN	0.0725	3.6809 (0.1)	2.1584	3.6874
	GARCHCCN	0.0950	0.1128	2.2385	0.1885
	0.05				
	GARCH	0.0325	2.9278	1.3000	6.4033(0.05)
	GARCHTN	0.0325	2.9278	1.2551	6.4033(0.05)
	GARCHCN	0.0325	2.9278	1.2891	6.4033(0.05)
	GARCHCCN	0.0450	0.2175	1.3096	1.6191
	0.025				
	GARCH	0.0125	3.1324	0.9065	7.1809(0.05)
	GARCHTN	0.0125	3.1324	0.8756	7.1809(0.05)
	GARCHCN	0.0125	3.1324	0.8984	7.1809(0.05)
	GARCHCCN	0.0150	1.9110	0.8643	3.2002
LVMH	0.1				
	GARCH	0.0725	3.6809 (0.1)	1.4533	4.0765
	GARCHTN	0.0750	3.0143 (0.1)	1.4139	3.2786
	GARCHCN	0.0750	3.0143 (0.1)	1.4139	3.2786
	GARCHCCN	0.0750	3.0143 (0.1)	1.4433	3.2786
	0.05				
	GARCH	0.0375	1.4350	0.7931	1.7357
	GARCHTN	0.0375	1.4350	0.7735	1.7357
	GARCHCN	0.0375	1.4350	0.7735	1.7357
	GARCHCCN	0.0400	0.9014	0.7852	1.0893
	0.025				
	GARCH	0.0300	0.3860	0.4525	1.2187
	GARCHTN	0.0300	0.3860	0.4427	1.2187
	GARCHCN	0.0300	0.3860	0.4427	1.2187
	GARCHCCN	0.0300	0.3860	0.4443	1.2187

Table H.0.3: Fitted Models

Parameters	Data	4 different GARCH models			
5 Taiwanese Stocks					
	Acer	G	GTN	GCN	GCCN
κ		0.0649**	0.0545	0.0547*	0.0942***
		(0.0215)	(1.3283)	(0.0209)	(0.0267)
α		0.9428***	0.9337*	0.9453***	0.9430***
		(0.0096)	(0.4514)	(0.0090)	(0.0125)
β		0.0473***	0.0663***	0.0480***	0.0263***
		(0.0074)	(0.1972)	(0.0069)	(0.0056)
l_1					0.7586***
					(0.0128)
r_1					0.8504***
					(0.0089)
m_1					−0.9022***
					(0.1518)
m_2					2.9185***
					(0.3093)
-LOGL		8.2309e+003	8.1623e+003	8.2288e+003	7.8975e+003
BIC		1.6486e+004	1.6349e+004	1.6376e+004	1.5852e+004
	ChinaTrust	G	GTN	GCN	GCCN
κ		0.0358***	0.0255***	0.0334***	0.0690***
		(0.0099)	(0.0089)	(0.0043)	(0.0155)
α		0.9387***	0.9376***	0.9397***	0.9350***
		(0.0079)	(0.0079)	(0.0025)	(0.0097)
β		0.0530***	0.0616***	0.0535***	0.0314***

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Table H.0.3 – continued from previous page

Parameters	Data	4 different GARCH models			
		(0.0068)	(0.0079)	(0.0029)	(0.0044)
l_1					0.6459***
					(0.0160)
r_1					0.8499***
					(0.0127)
m_1					−0.2178*
					(0.1043)
m_2					3.2807***
					(0.4655)
-LOGL		6.1672e+003	6.1378e+003	6.1664e+003	5.9512e+003
BIC		1.2359e+004	1.2300e+004	1.2357e+004	1.1958e+004
	Clevo	G	GTN	GCN	GCCN
κ		0.1088***	0.1222	0.1057***	0.1578***
		(0.0257)	(270.9143)	(0.0260)	(0.0286)
α		0.9143***	0.8936	0.9138***	0.9068***
		(0.0114)	(59.4321)	(0.0114)	(0.0118)
β		0.0716***	0.1064	0.0741***	0.0447***
		(0.0093)	(1.5803)	(0.0095)	(0.0056)
l_1					0.8208***
					(0.0106)
r_1					0.8494***
					(0.0080)
m_1					−1.8123***
					(0.2189)
m_2					2.9940***
					(0.2684)
-LOGL		8.9054e+003	8.7897e+003	8.9023e+003	8.4059e+003
BIC		1.7836e+004	1.7604e+004	1.7829e+004	1.6869e+004
	Fubon	G	GTN	GCN	GCCN
κ		0.0494***	0.0426***	0.0480***	0.0827***
		(0.0151)	(0.0140)	(0.0177)	(0.0211)
α		0.9378***	0.9363***	0.9368***	0.9336***
		(0.0110)	(0.0112)	(0.0121)	(0.0136)
β		0.0486***	0.0548***	0.0515***	0.0280***
		(0.0080)	(0.0092)	(0.0086)	(0.0056)
l_1					0.6764***
					(0.0152)
r_1					0.8692***
					(0.0143)
m_1					−0.5079***
					(0.1422)
m_2					4.1510***
					(0.7095)
-LOGL		6.2292e+003	6.2155e+003	6.2283e+003	6.0623e+003
BIC		1.2483e+004	1.2455e+004	1.2481e+004	1.2181e+004
	Formosa	G	GTN	GCN	GCCN

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Table H.0.3 – continued from previous page

Parameters	Data	4 different GARCH models			
	Petrochemical Corp				
κ		0.0143***	0.0141***	0.0098***	0.0217***
		(0.0053)	(0.0049)	(0.0042)	(0.0064)
α		0.9539***	0.9526***	0.9551***	0.9582***
		(0.0078)	(0.0077)	(0.0083)	(0.0093)
β		0.0406***	0.0425***	0.0433***	0.0203***
		(0.0069)	(0.0069)	(0.0079)	(0.0048)
l_1					0.4680***
					(0.0167)
r_1					0.4608***
					(0.0161)
m_1					0.4761***
					(0.0933)
m_2					−0.4757***
					(0.0889)
-LOGL		4.6908e+003	4.6890e+003	4.6876e+003	4.5876e+003
BIC		9.4052e+003	9.4015e+003	9.3784e+03	9.2319e+003
5 Chinese Stocks					
	TsingHua TongFang	G	GTN	GCN	GCCN
κ		0.1691***	0.1651***	0.1611***	0.2214***
		(0.0425)	(0.0420)	(0.0223)	(0.0601)
α		0.9174***	0.9135***	0.9181***	0.9081***
		(0.0132)	(0.0132)	(0.0076)	(0.0207)
β		0.0606***	0.0682***	0.0633***	0.0301***
		(0.0092)	(0.0100)	(0.0067)	(0.0065)
l_1					0.5086***
					(0.0130)
r_1					0.6967***
					(0.0163)
m_1					0.1584***
					(0.0490)
m_2					0.6861***
					(0.1296)
-LOGL		8.0344e+003	8.0233e+003	8.0362e+003	7.8094e+003
BIC		1.6093e+004	1.6071e+004	1.6097e+004	1.5676e+004
	GDPower	G	GTN	GCN	GCCN
κ		0.1013***	0.1011***	0.4808***	0.0741***
		(0.0266)	(0.0270)	(0.4655e-004)	(0.0202)
α		0.9254***	0.9239***	0.7789***	0.9135***
		(0.0130)	(0.0129)	(0.4660e-004)	(0.0188)
β		0.0535***	0.0559***	0.1309***	0.0272***
		(0.0088)	(0.0086)	(0.0124e-004)	(0.0060)

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Table H.0.3 – continued from previous page

Parameters	**Data**	**4 different GARCH models**			
l_1					0.2896^{***}
					(0.0079)
r_1					0.3031^{***}
					(0.0078)
m_1					0.4585^{***}
					(0.0341)
m_2					-0.4375^{***}
					(0.0311)
-LOGL		7.2625e+003	7.2597e+003	7.2917e+003	7.0219e+003
BIC		1.4549e+004	1.4544e+004	1.4608e+004	1.4101e+004
	Inner Mongolia Baotou	G	GTN	GCN	GCCN
κ		0.1577^{***}	0.1586^{***}	0.2095^{***}	0.1990^{***}
		(0.0444)	(0.0467)	(0.0452)	(0.0440)
α		0.8923^{***}	0.8829^{***}	0.8598^{***}	0.8848^{***}
		(0.0175)	(0.0194)	(0.0185)	(0.0209)
β		0.0874^{***}	0.1024^{***}	0.1136^{***}	0.0348^{***}
		(0.0134)	(0.0166)	(0.0163)	(0.0063)
l_1					0.4227^{***}
					(0.0123)
r_1					0.5363^{***}
					(0.0131)
m_1					0.2933^{***}
					(0.0465)
m_2					0.1237^{***}
					(0.0624)
-LOGL		7.0232e+003	7.0136e+003	7.0299e+003	6.7681e+003
BIC		1.4071e+004	1.4051e+004	1.4084e+004	1.3592e+004
	China Merchants Bank	G	GTN	GCN	GCCN
κ		0.0598^{***}	0.0625^{***}	0.0766^{***}	0.0736^{***}
		(0.0204)	(0.0214)	(0.0237)	(0.0204)
α		0.9228^{***}	0.9135^{***}	0.9112^{***}	0.9480^{***}
		(0.0154)	(0.0163)	(0.0163)	(0.0118)
β		0.0686^{***}	0.0810^{***}	0.0789^{***}	0.0216^{***}
		(0.0144)	(0.0168)	(0.0158)	(0.0053)
l_1					0.4752^{***}
					(0.0174)
r_1					0.7375^{***}
					(0.0272)
m_1					0.1700^{***}
					(0.0601)
m_2					1.0129^{***}
					(0.2860)
-LOGL		4.0357e+03	4.0311e+03	4.1011e+003	3.9846e+003

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Table H.0.3 – continued from previous page

Parameters	Data	4 different GARCH models			
BIC		8.0939e+03	8.0847e+03	8.2247e+003	7.9188e+03
	ShangHai International Airport	G	GTN	GCN	GCCN
κ		0.1256***	0.1279***	0.3463***	0.1408***
		(0.0208)	(0.0221)	(0.3554e-004)	(0.0230)
α		0.8885***	0.8850***	0.7854***	0.8432***
		(0.0123)	(0.0134)	(0.0346e-004)	(0.0208)
β		0.0835***	0.0884***	0.1502***	0.0459***
		(0.0095)	(0.0107)	(0.3255e-004)	(0.0075)
l_1					0.2919***
					(0.0078)
r_1					0.3474***
					(0.0087)
m_1					0.4288***
					(0.0371)
m_2					−0.2847***
					(0.0390)
-LOGL		6.7237e+03	6.7196e+03	6.7445e+003	6.4288e+003
BIC		1.3472e+04	1.3464e+04	1.3513e+004	1.2914e+004
5 Korean Stocks					
	Naver	G	GTN	GCN	GCCN
κ		0.0737***	0.0727***	0.7982***	0.0815***
		(0.0254)	(0.0250)	(0.0002)	(0.0259)
α		0.9622***	0.9621***	0.8228***	0.9617***
		(0.0065)	(0.0064)	(0.0001)	(0.0078)
β		0.0291***	0.0294***	0.0893***	0.0207***
		(0.0046)	(0.0046)	(0.0053)	(0.0042)
l_1					0.3859***
					(0.0176)
r_1					0.4220***
					(0.0140)
m_1					0.4920***
					(0.0496)
m_2					−0.3290***
					(0.0401)
-LOGL		7.0931e+003	7.0926e+003	7.1202e+003	7.0473e+003
BIC		1.4119e+004	1.4209e+004	1.4264e+004	1.4150e+004
	Samsung	G	GTN	GCN	GCCN
κ		0.0188***	0.0162***	0.0090***	0.0333***
		(1.8834e-008)	(0.0063)	(0.0041)	(0.0089)
α		0.9638***	0.9648***	0.9677***	0.9645***

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Table H.0.3 – continued from previous page

Parameters	Data	4 different GARCH models			
		(1.050e-004)	(0.0046)	(0.0044)	(0.0056)
β		0.0326***	0.0323***	0.0317***	0.0237***
		(8.9954e-004)	(0.0043)	(0.0042)	(0.0039)
l_1					0.3294***
					(0.0128)
r_1					0.4928***
					(0.0221)
m_1					0.4559***
					(0.0491)
m_2					−0.2842***
					(0.0698)
-LOGL		7.8545e+03	7.8540e+003	7.8515e+003	7.8109e+003
BIC		1.5734e+004	1.5733e+004	1.5728e+004	1.5679e+004
	Willbes	G	GTN	GCN	GCCN
κ		0.2310***	0.2326***	0.2016***	0.2303***
		(0.0510)	(0.0465)	(0.0502)	(0.0413)
α		0.9015***	0.8937***	0.9032***	0.8942***
		(0.0131)	(0.0129)	(0.0112)	(0.0156)
β		0.0823***	0.0952***	0.0884***	0.0293***
		(0.0111)	(0.0122)	(0.0044)	(0.0049)
l_1					0.3116***
					(0.0075)
r_1					0.3866***
					(0.0089)
m_1					0.2257***
					(0.0201)
m_2					−0.0965***
					(0.0232)
-LOGL		9.6492e+003	9.6334e+003	9.6453e+003	9.2641e+003
BIC		1.9323e+004	1.9292e+004	1.9315e+004	1.8586e+004
	Enex	G	GTN	GCN	GCCN
κ		0.2292***	0.2374***	0.2298***	0.1998***
		(0.0427)	(0.0437)	(0.0117)	(0.0342)
α		0.9075***	0.9019***	0.9067***	0.8507***
		(0.0115)	(0.0122)	(0.7098-003)	(0.0204)
β		0.0754***	0.0829***	0.0769***	0.0457***
		(0.0098)	(0.0110)	(0.0099)	(0.0082)
l_1					0.7704***
					(0.0057)
r_1					0.7372***
					(0.0064)
m_1					0.3296***
					(0.0167)
m_2					−0.2754***

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Table H.0.3 – continued from previous page

Parameters	Data	4 different GARCH models			
					(0.0164)
-LOGL		9.6209e+003	9.6146e+003	9.6197e+003	9.2278e+03
BIC		1.9267e+004	1.9254e+004	1.9264e+004	1.8513e+04
	Posco	G	GTN	GCN	GCCN
κ		0.0327***	0.0327***	0.0250***	0.0485***
		(0.0091)	(0.0090)	(0.0077)	(0.0109)
α		0.9377***	0.9372***	0.9398***	0.9406***
		(0.0069)	(0.0070)	(0.0070)	(0.0080)
β		0.0572***	0.0579***	0.0586***	0.0384***
		(0.0066)	(0.0067)	(0.0067)	(0.0054)
l_1					0.2889***
					(0.0100)
r_1					0.3872***
					(0.0149)
m_1					0.5049***
					(0.0479)
m_2					−0.4136***
					(0.0547)
-LOGL		7.6623e+003	7.6616e+03	7.6596e+003	7.6010e+003
BIC		1.5349e+004	1.5348e+04	1.5344e+004	1.5259e+004
5 French Stocks					
	BNP	G	GTN	GCN	GCCN
κ		0.0366***	0.0308***	0.0357***	0.0412***
		(0.0096)	(0.0088)	(0.0090)	(0.0095)
α		0.9210***	0.9194***	0.9192***	0.9186***
		(0.0087)	(0.0088)	(0.0083)	(0.0083)
β		0.0726***	0.0788***	0.0755***	0.0723***
		(0.0081)	(0.0089)	(0.0076)	(0.0075)
l_1					0.9994***
					(0.0001)
r_1					0.9990***
					(0.0001)
m_1					−1.3708e+ 003***
					(141.4291)
m_2					791.3239***
					(81.8575)
-LOGL		7.6824e+003	7.6673e+003	7.6675e+003	7.4894e+003
BIC		1.5390e+004	1.5359e+004	1.5360e+004	1.5036e+004
	Danone	G	GTN	GCN	GCCN
κ		0.0377***	0.0376***	0.0347***	0.0518***
		(0.0071)	(0.0071)	(0.0073)	(0.0097)
α		0.9164***	0.9161***	0.9165***	0.9044***
		(0.0080)	(0.0081)	(0.0077)	(0.0132)
β		0.0684***	0.0690***	0.0724***	0.0468***
		(0.0070)	(0.0072)	(0.0071)	(0.0071)
l_1					0.2943***

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Table H.0.3 – continued from previous page

Parameters	Data	4 different GARCH models			
					(0.0096)
r_1					0.3070***
					(0.0089)
m_1					0.6965***
					(0.0643)
m_2					−0.6513***
					(0.0546)
-LOGL		6.4871e+003	6.4867e+003	6.4882e+003	6.3608e+003
BIC		1.2999e+004	1.2998e+004	1.3001e+004	1.2779e+004
	Gemalto	G	GTN	GCN	GCCN
κ		0.1109***	0.1097***	0.1061***	0.0950***
		(0.0359)	(0.0366)	(0.0301)	(0.0312)
α		0.9446***	0.9446***	0.9465***	0.9345***
		(0.0129)	(0.0132)	(0.0106)	(0.0163)
β		0.0313***	0.0318***	0.0306***	0.0232***
		(0.0067)	(0.0067)	(0.0054)	(0.0054)
l_1					0.4937***
					(0.0202)
r_1					0.3777***
					(0.0132)
m_1					0.1709*
					(0.0991)
m_2					−0.4765***
					(0.0473)
-LOGL		4.9645e+003	4.9640e+003	4.9693e+003	4.8288e+003
BIC		9.9522e+003	9.9512e+003	9.9618e+03	9.7117e+003
	Vallourec	G	GTN	GCN	GCCN
κ		0.1251***	0.1194***	0.1242***	0.0881***
		(0.0303)	(0.0284)	(0.0165)	(0.0265)
α		0.9363***	0.9124***	0.9122***	0.9254***
		(0.0135)	(0.0121)	(0.0073)	(0.0166)
β		0.0658***	0.0714***	0.0711***	0.0343***
		(0.0101)	(0.0098)	(0.0080)	(0.0076)
l_1					0.5893***
					(0.0118)
r_1					0.5798***
					(0.0114)
m_1					0.3772***
					(0.0406)
m_2					−0.3572***
					(0.0367)
-LOGL		8.3739e+003	8.3659e+003	8.3768e+003	8.2304e+03
BIC		1.6772e+004	1.6756e+004	1.6778e+004	1.6518e+04
	LVMH	G	GTN	GCN	GCCN
κ		0.0342***	0.0331***	0.0236***	0.0515***
		(0.0082)	(0.0083)	(0.0061)	(0.0119)
α		0.9276***	0.9266***	0.9285***	0.9254***

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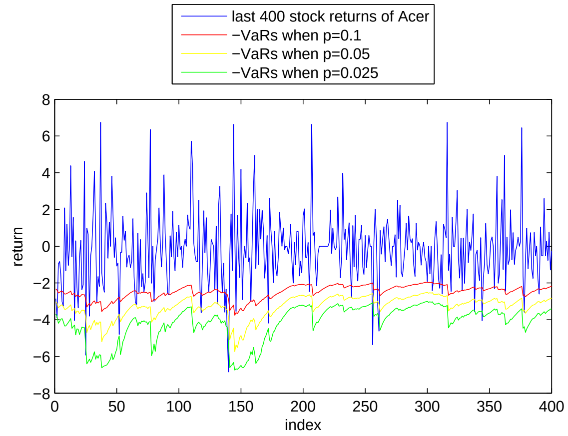
Table H.0.3 – continued from previous page

Parameters	Data	4 different GARCH models			
		(0.0079)	(0.0236)	(0.0077)	(0.0109)
β		0.0633^{***}	0.0654^{***}	0.0698^{***}	0.0482^{***}
		(0.0071)	(0.0074)	(0.0074)	(0.0071)
l_1					0.4603^{***}
					(0.0207)
r_1					0.4678^{***}
					(0.0155)
m_1					0.4865^{***}
					(0.0758)
m_2					-0.3970^{***}
					(0.0638)
-LOGL		7.2992e+003	7.2962e+003	7.2930e+003	7.2512e+003
BIC		1.4623e+004	1.4617e+004	1.4433e+04	1.4560e+004

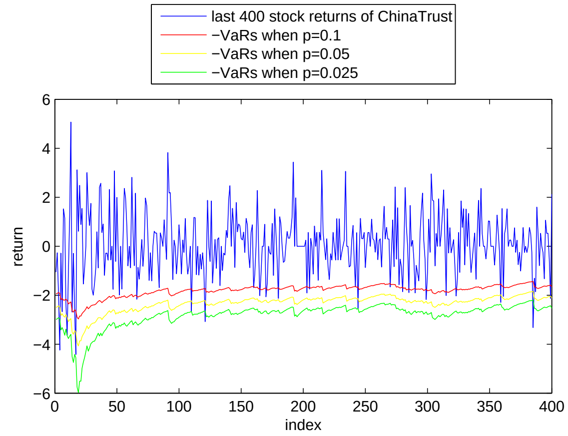
Notes: $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$

Table H.0.2: Data used in Table H.0.3

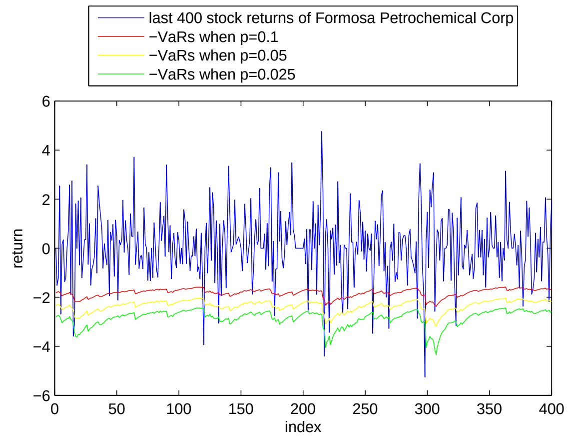
Acer	From January 4, 2000 to June 24, 2014
ChinaTrust	From May 16, 2002 to June 24, 2014
Clevo	From January 4, 2000 to May 13, 2015
Fubon	From December 20, 2001 to June 24, 2014
Formosa Petrochemical Corp	From December 26, 2003 to June 24, 2014
Chinese stocks	
TsingHuaTongFang	From January 27, 2000 to June 24, 2014
GD power	From January 18, 2000 to June 24, 2014
Inner Mongolia Baotou	From March 9, 2001 to May 16, 2014
China Merchants Bank	From December 1, 2006 to June 24, 2014
ShangHai International Air Port	From July 29, 2000, 2000 to June 24, 2014
Korean stocks	
Naver	From October 29, 2002 to June 24, 2014
Samsung	From January 4, 2000 to June 24, 2014
Willbes	From January 4, 2000 to May 24, 2015
Enex	From January 4, 2000 to May 24, 2015
Posco	From January 4, 2000 to June 24, 2014
French stocks	
BNP	From January 3, 2000 to June 25, 2014
Danone	From January 3, 2000 to June 25, 2014
Gemalto	From May 18, 2004 to June 25, 2014
Vallourec	From January 3, 2000 to June 27, 2014
LVMH	From January 3, 2000 to June 25, 2014



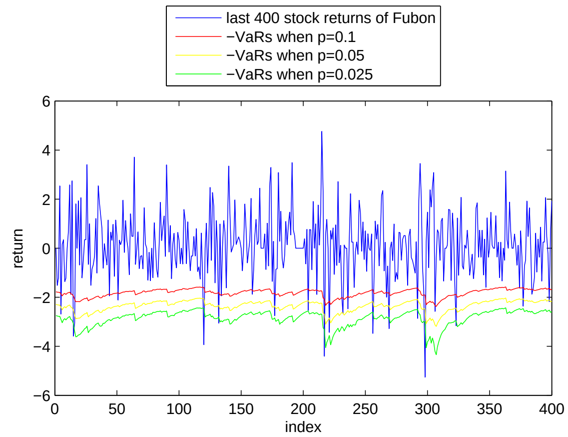
(a) *VaRs of Acer*



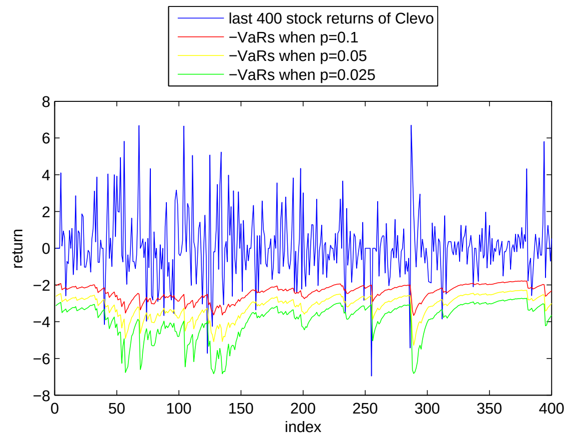
(b) *VaRs of ChinaTrust*



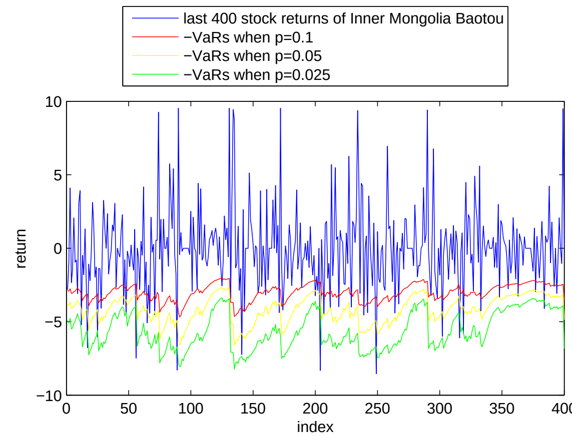
(c) *VaRs of Formosa Petrochemical Corp*



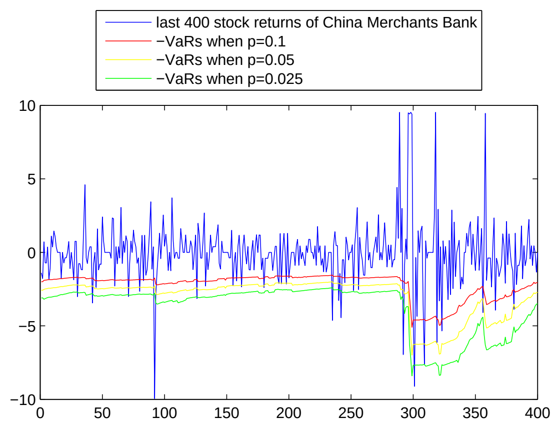
(d) *VaRs of Fubon*



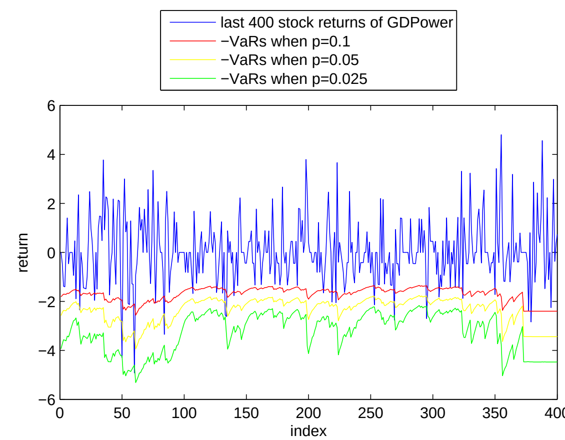
(a) *VaRs of Clevo*



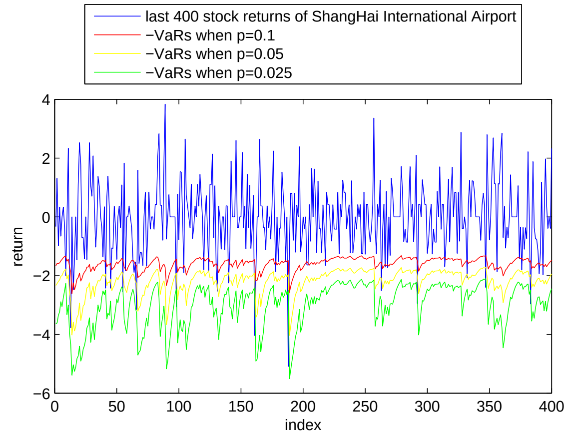
(b) *VaRs of Inner Mongolia Baotou*



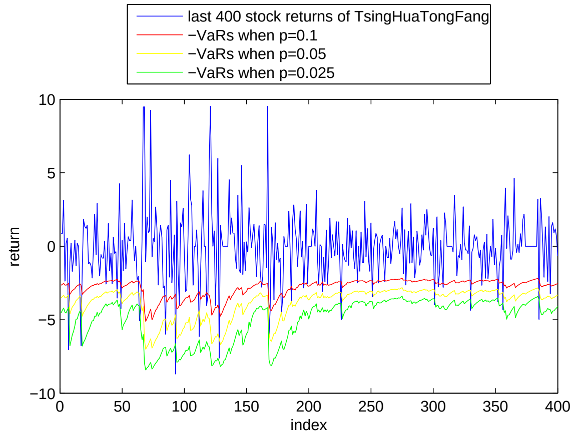
(c) *VaRs of China Merchants Bank*



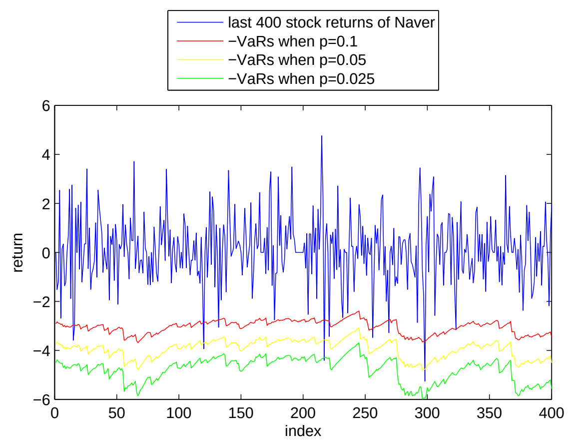
(d) *VaRs of GDPower*



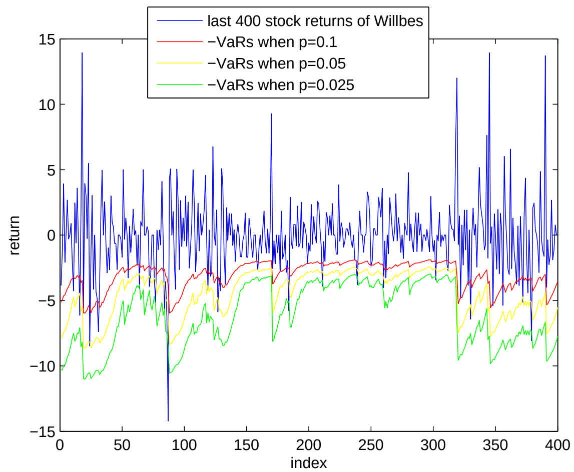
(a) *VaRs of ShangHai International Airport*



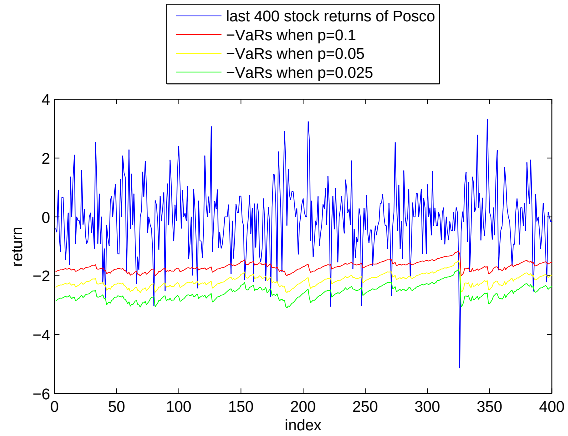
(b) *VaRs of TsingHuaTongFang*



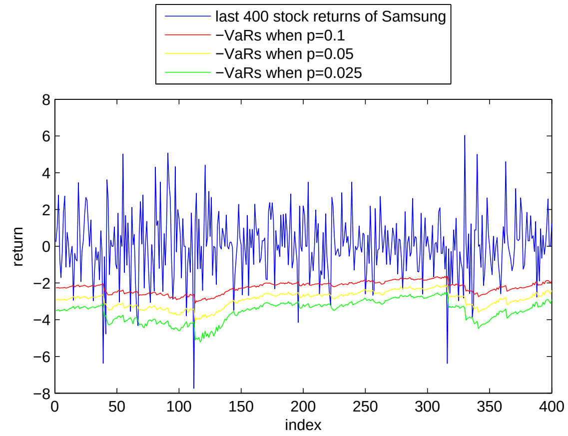
(c) *VaRs of Naver*



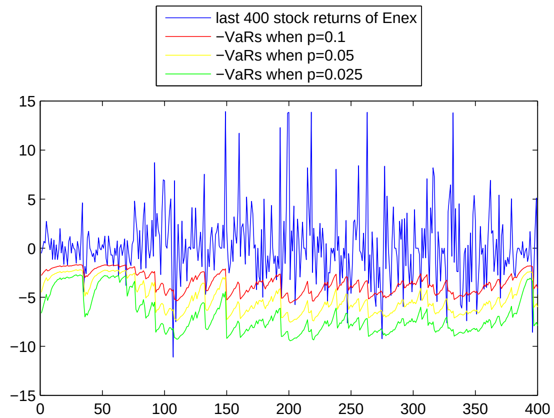
(d) *VaRs of Willbes*



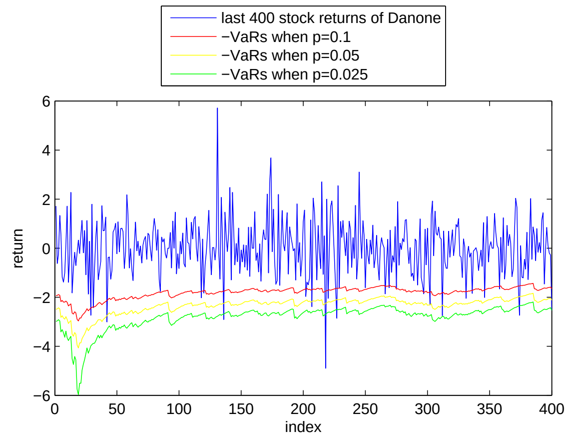
(a) *VaRs of Posco*



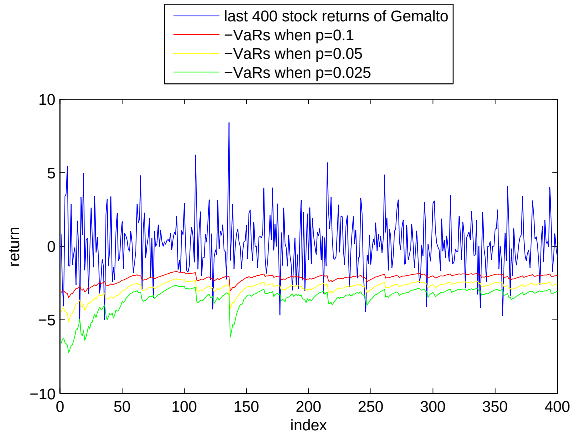
(b) *VaRs of Samsung*



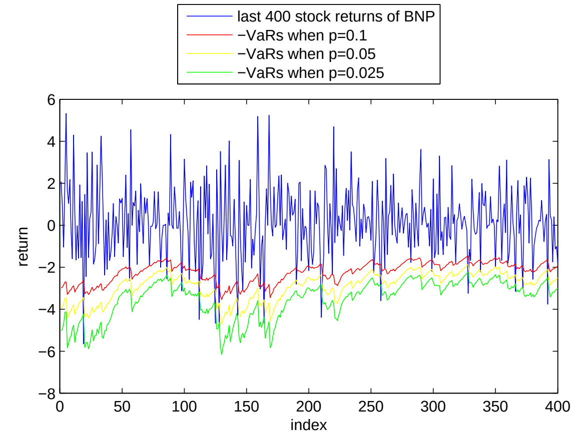
(c) *VaRs of Enex*



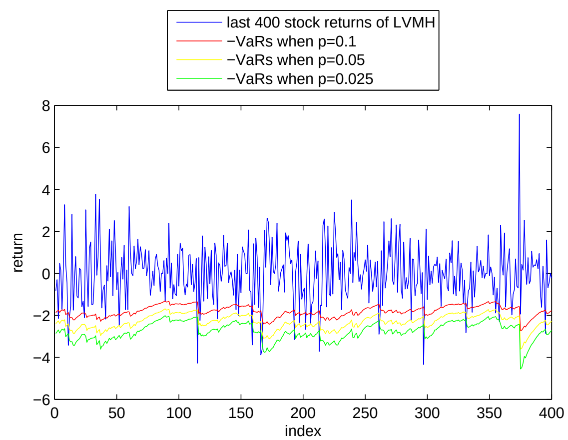
(d) *VaRs of Danone*



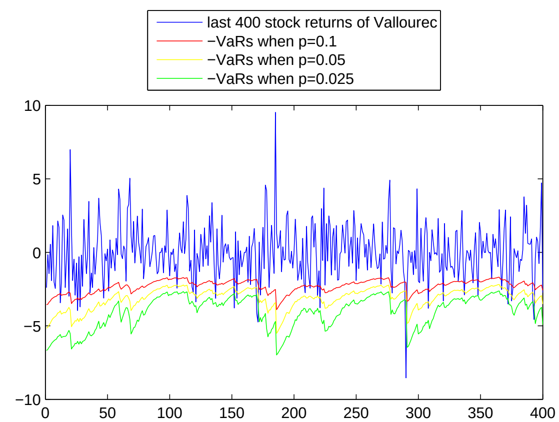
(a) *VaRs of Gemalto*



(b) *VaRs of BNP*



(c) *VaRs of LVMH*



(d) *VaRs of Vallourec*

Appendix I

Empirical Performance: In-sample VaR test statistics

Table I.0.1: Derive relative bounds from the fitted GARCHCCN for each stock

stocks	$\sqrt{\kappa/(1-\alpha-\beta)}$	σ	$Lower/\sigma$	$Upper/\sigma$	Ω	pm
Acer	1.7517	2.3620	-3.0725	2.8645	1.0849	0.9058
ChinaTrust	1.4330	1.5484	-4.6869	4.3697	1.0099	0.9889
Clevo	1.8038	2.0766	-3.4947	3.2581	1.0397	0.9571
Fubon	1.4675	1.5488	-4.6856	4.3684	1.0086	0.9907
Formosa Petrochemical Corp	1.0046	1.4898	-4.8713	4.5416	1.0576	0.9177
TsingHuaTongFang	1.8928	2.2069	-4.7742	4.3188	1.0425	0.9507
GDPower	1.1178	1.0778	-9.7755	8.8430	1.0302	0.9648
Inner Mongolia Baotou	1.5733	2.1091	-4.9955	4.5190	1.0917	0.8931
China Merchants Bank	1.5560	1.6620	-6.3396	5.7348	1.0083	0.9905
Shanghai International Airport	1.1268	1.1500	-9.1621	8.2881	1.0320	0.9634
Naver	2.1519	2.8884	-5.6267	4.8388	1.0394	0.9279
Samsung	1.6799	1.9391	-8.3809	7.2074	1.0080	0.9890
Willbes	1.7348	1.8059	-8.9994	7.7392	1.0284	0.9686
Enex	1.3891	1.3891	-11.6995	10.0612	1.0000	1.0000
Posco	1.5197	1.5940	-10.1957	8.7680	1.0063	0.9918
BNP	2.1278	2.1311	-4.9439	4.4723	1.0000	1.0000
Danone	1.0303	1.0723	-9.8259	8.8886	1.0166	0.9786
Gemalto	1.4986	1.7869	-5.8964	5.3339	1.0039	0.9949
Vallourec	1.4785	1.4871	-7.0851	6.4092	1.0006	0.9993
LVMH	1.3967	1.4774	-7.1315	6.4512	1.0068	0.9915

Table I.0.2: In-sample VaR test statistics

Data	**p**	x/T	**Kupiec LR test**	$E(shortfall^2)$
Acer	0.1			
	GARCH	0.0951	0.9498	3.3117
	GARCHTN	0.0923	2.3859	3.4154
	GARCHCN	0.0926	2.2124	3.2548
	GARCHCCN	0.1036	0.4991	3.3527
	0.05			
	GARCH	0.0495	0.0162	2.6802
	GARCHTN	0.0540	1.1902	2.5732
	GARCHCN	0.0484	0.1911	2.5908
	GARCHCCN	0.0509	0.0661	2.3867
	0.025			
	GARCH	0.0290	2.2086	2.0424
	GARCHTN	0.0355	14.1530 $R_{0.01}$	1.8667
	GARCHCN	0.0273	0.7496	2.0295
	GARCHCCN	0.0256	0.0542	1.5580
ChinaTrust	0.1			
	GARCH	0.0830	10.1636 $R_{0.01}$	2.9705
	GARCHTN	0.0823	11.0030 $R_{0.01}$	3.0877
	GARCHCN	0.0816	11.8777 $R_{0.01}$	3.0644
	GARCHCCN	0.0903	3.1983	3.0298
	0.05			
	GARCH	0.0482	0.2117	2.4258
	GARCHTN	0.0509	0.0456	2.2953
	GARCHCN	0.0482	0.2117	2.3171
	GARCHCCN	0.0509	0.0456	2.2337
	0.025			
	GARCH	0.0291	1.9660	2.0571
	GARCHTN	0.0335	7.9409 $R_{0.01}$	1.7152
	GARCHCN	0.0298	2.6383	1.8813
	GARCHCCN	0.0308	3.8198	1.4508
Clevo	0.1			
	GARCH	0.0849	9.9742 $R_{0.01}$	3.3307
	GARCHTN	0.0852	9.6176 $R_{0.01}$	3.5349
	GARCHCN	0.0841	11.0851 $R_{0.01}$	3.2520
	GARCHCCN	0.0961	0.6536	3.0807
	0.05			
	GARCH	0.0502	0.0020	2.0552
	GARCHTN	0.0557	2.5175	2.1632
	GARCHCN	0.0494	0.0323	2.0018

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Table I.0.2 – continued from previous page

Data	**p**	x/T	**Kupiec LR test**	$E(shortfall^2)$
	GARCHCCN	0.0504	0.0143	1.8646
	0.025			
	GARCH	0.0257	0.0845	1.6277
	GARCHTN	0.0398	28.8164$R_{0.01}$	1.2725
	GARCHCN	0.0263	0.2468	1.5319
	GARCHCCN	0.0284	1.7101	1.2548
Fubon	0.1			
	GARCH	0.0834	9.9595$R_{0.01}$	3.2704
	GARCHTN	0.0811	12.9687$R_{0.01}$	3.3797
	GARCHCN	0.0805	13.9064$R_{0.01}$	3.2857
	GARCHCCN	0.0921	2.1625	3.0716
	0.05			
	GARCH	0.0532	0.6563	2.6959
	GARCHTN	0.0522	0.3207	2.7310
	GARCHCN	0.0526	0.2350	2.6158
	GARCHCCN	0.0519	0.4196	2.5364
	0.025			
	GARCH	0.0305	3.5778	2.6338
	GARCHTN	0.0311	4.4393$R_{0.05}$	2.5934
	GARCHCN	0.0292	2.1198	2.6299
	GARCHCCN	0.0260	0.1144	2.3864
Formosa Petrochemical Corp	0.1			
	GARCH	0.0836	8.1409$R_{0.01}$	2.0322
	GARCHTN	0.0832	8.5405$R_{0.01}$	2.0278
	GARCHCN	0.0805	11.6246$R_{0.01}$	1.9975
	GARCHCCN	0.0991	0.0248	2.1614
	0.05			
	GARCH	0.0445	1.7032	2.0532
	GARCHTN	0.0445	1.7032	2.0532
	GARCHCN	0.0441	1.9567	1.9426
	GARCHCCN	0.0546	1.1031	1.9762
	0.025			
	GARCH	0.0271	0.4509	1.9338
	GARCHTN	0.0267	0.3008	1.9373
	GARCHCN	0.0263	0.1805	1.8010
	GARCHCCN	0.0302	2.6765	1.5418
TsingHuaTongFang	0.1			
	GARCH	0.0815	13.5996$R_{0.01}$	6.1295
	GARCHTN	0.0806	14.9844$R_{0.01}$	6.0762
	GARCHCN	0.0794	16.9429$R_{0.01}$	6.0693

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Table I.0.2 – continued from previous page

Data	**p**	x/T	**Kupiec LR test**	$E(shortfall^2)$
	GARCHCCN	0.1023	0.1890	6.0687
	0.05			
	GARCH	0.0477	0.3754	5.4054
	GARCHTN	0.0468	0.7292	5.4207
	GARCHCN	0.0453	1.5855	5.4210
	GARCHCCN	0.0525	0.4206	4.9382
	0.025			
	GARCH	0.0314	5.2772$R_{0.025}$	4.4233
	GARCHTN	0.0311	4.8169$R_{0.05}$	4.4317
	GARCHCN	0.0299	3.1738	4.3764
	GARCHCCN	0.0268	0.4482	3.5460
GDPower	0.1			
	GARCH	0.0727	30.5586$R_{0.01}$	5.3707
	GARCHTN	0.0727	30.5586$R_{0.01}$	5.3388
	GARCHCN	0.0713	34.1503$R_{0.01}$	5.3961
	GARCHCCN	0.1032	0.3796	5.0453
	0.05			
	GARCH	0.0417	5.1971$R_{0.025}$	5.7026
	GARCHTN	0.0417	5.1971$R_{0.025}$	5.6691
	GARCHCN	0.0417	5.1971$R_{0.025}$	5.5201
	GARCHCCN	0.0517	0.2143	5.4002
	0.025			
	GARCH	0.0272	0.6548	5.7173
	GARCHTN	0.0275	0.8394	5.3579
	GARCHCN	0.0275	0.8394	5.3579
	GARCHCCN	0.0234	0.3819	6.1380
Inner Mongolia Baotou	0.1			
	GARCH	0.0764	20.5877$R_{0.01}$	5.0173
	GARCHTN	0.0755	22.3974$R_{0.01}$	4.9469
	GARCHCN	0.0797	15.1462$R_{0.01}$	4.8451
	GARCHCCN	0.1065	1.4406	5.3324
	0.05			
	GARCH	0.0408	5.8513$R_{0.025}$	5.1157
	GARCHTN	0.0405	6.2854$R_{0.025}$	5.0203
	GARCHCN	0.0408	5.8513$R_{0.025}$	5.1768
	GARCHCCN	0.0495	0.0134	5.4212
	0.025			
	GARCH	0.0256	0.0427	4.7686
	GARCHTN	0.0256	0.0427	4.6652
	GARCHCN	0.0272	0.5975	4.5871

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Table I.0.2 – continued from previous page

Data	p	x/T	Kupiec LR test	$E(shortfall^2)$
	GARCHCCN	0.0243	0.0649	4.9679
China Merchants Bank	0.1			
	GARCH	0.0686	22.1747$R_{0.01}$	8.9734
	GARCHTN	0.0884	2.8413	5.3272
	GARCHCN	0.0862	4.0435	5.2491
	GARCHCCN	0.1015	0.0476	5.6845
	0.05			
	GARCH	0.0445	1.2224	8.1432
	GARCHTN	0.0532	0.3942	4.7670
	GARCHCN	0.0499	0.0001	4.8506
	GARCHCCN	0.0494	0.0140	4.8870
	0.025			
	GARCH	0.0313	2.7374	6.9754
	GARCHTN	0.0302	1.8878	4.9276
	GARCHCN	0.0296	1.5190	4.7446
	GARCHCCN	0.0258	0.0469	4.0412
ShangHai International Airport	0.1			
	GARCH	0.0677	42.2451$R_{0.01}$	7.1642
	GARCHTN	0.0744	25.8015$R_{0.01}$	4.9776
	GARCHCN	0.0686	39.7353$R_{0.01}$	5.2624
	GARCHCCN	0.1103	3.7087	4.4723
	0.05			
	GARCH	0.0435	3.0398	7.4825
	GARCHTN	0.0426	3.9842$R_{0.05}$	5.5467
	GARCHCN	0.0389	9.1437$R_{0.01}$	5.8427
	GARCHCCN	0.0515	0.1442	5.3864
	0.025			
	GARCH	0.0294	2.4598	7.8088
	GARCHTN	0.0263	0.2364	6.2906
	GARCHCN	0.0251	0.0018	6.2935
	GARCHCCN	0.0270	0.4982	5.7380
Naver	0.1			
	GARCH	0.0788	15.3786$R_{0.01}$	6.3113
	GARCHTN	0.0763	19.2829$R_{0.01}$	4.8982
	GARCHCN	0.0728	25.7047$R_{0.01}$	5.0526
	GARCHCCN	0.0924	1.9012	5.0678
	0.05			
	GARCH	0.0418	4.2624$R_{0.05}$	6.6205
	GARCHTN	0.0387	8.3515$R_{0.01}$	4.6237
	GARCHCN	0.0383	8.8975$R_{0.01}$	4.5749

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Table I.0.2 – continued from previous page

Data	p	x/T	Kupiec LR test	$E(shortfall^2)$
	GARCHCCN	0.0464	0.8205	5.0013
	0.025			
	GARCH	0.0244	0.0429	6.8016
	GARCHTN	0.0237	0.2019	3.7594
	GARCHCN	0.0202	2.8793	4.3745
	GARCHCCN	0.0258	0.0733	4.3209
Samsung	0.1			
	GARCH	0.0869	7.0759$R_{0.01}$	6.9308
	GARCHTN	0.0838	10.9129$R_{0.01}$	4.7463
	GARCHCN	0.0805	16.1075$R_{0.01}$	4.4981
	GARCHCCN	0.0894	4.5739 $R_{0.05}$	4.9211
	0.05			
	GARCH	0.0474	0.5247	8.5990
	GARCHTN	0.0468	0.7761	4.8898
	GARCHCN	0.0449	2.0555	4.4391
	GARCHCCN	0.0477	0.4177	5.1224
	0.025			
	GARCH	0.0300	3.4383	9.8307
	GARCHTN	0.0244	0.0548	5.9356
	GARCHCN	0.0224	1.0023	5.3419
	GARCHCCN	0.0221	1.2376	6.0537
Willbes	0.1			
	GARCH	0.0622	68.0018$R_{0.01}$	21.4107
	GARCHTN	0.0755	27.1432$R_{0.01}$	10.5803
	GARCHCN	0.0729	33.6828$R_{0.01}$	10.1558
	GARCHCCN	0.1085	2.9339	11.7413
	0.05			
	GARCH	0.0364	16.0428 $R_{0.01}$	24.5366
	GARCHTN	0.0404	7.7630$R_{0.01}$	10.8562
	GARCHCN	0.0383	11.7752$R_{0.01}$	10.2056
	GARCHCCN	0.0526	0.5452	11.7622
	0.025			
	GARCH	0.0237	0.2804	26.6092
	GARCHTN	0.0242	0.1009	10.8695
	GARCHCN	0.0223	1.1364	10.3367
	GARCHCCN	0.0261	0.1700	10.9409
Enex	0.1			
	GARCH	0.0601	76.6339$R_{0.01}$	15.8856
	GARCHTN	0.0798	17.0998$R_{0.01}$	10.4783
	GARCHCN	0.0675	49.2227 $R_{0.01}$	10.4121

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Table I.0.2 – continued from previous page

Data	**p**	x/T	**Kupiec LR test**	$E(shortfall^2)$
	GARCHCCN	0.1098	3.8893	10.1016
	0.05			
	GARCH	0.0367	15.4163 $R_{0.01}$	16.0602
	GARCHTN	0.0375	13.5417 $R_{0.01}$	10.2327
	GARCHCN	0.0372	14.1517 $R_{0.01}$	10.2739
	GARCHCCN	0.0508	0.0468	10.5361
	0.025			
	GARCH	0.0266	0.3784	14.3972
	GARCHTN	0.0670	50.9526 $R_{0.01}$	10.4783
	GARCHCN	0.0239	0.1814	9.3719
	GARCHCCN	0.0231	0.5557	10.8630
Posco	0.1			
	GARCH	0.0670	48.2572 $R_{0.01}$	6.4589
	GARCHTN	0.0802	16.5890 $R_{0.01}$	4.1277
	GARCHCN	0.0830	12.1114 $R_{0.01}$	4.2708
	GARCHCCN	0.0936	1.6364	4.5523
	0.05			
	GARCH	0.0362	15.8399 $R_{0.01}$	7.5835
	GARCHTN	0.0513	0.1266	3.8501
	GARCHCN	0.0485	0.1706	3.6675
	GARCHCCN	0.0527	0.5405	4.4388
	0.025			
	GARCH	0.0216	1.7861	8.7288
	GARCHTN	0.0275	0.8683	3.7422
	GARCHCN	0.0289	2.0955	4.1520
	GARCHCCN	0.0272	0.6850	4.5899
French Stocks				
BNP	0.1			
	GARCH	0.0728	33.1450 $R_{0.01}$	7.6076
	GARCHTN	0.0888	5.3025 $R_{0.01}$	3.3663
	GARCHCN	0.0885	5.5679 $R_{0.01}$	3.2873
	GARCHCCN	0.0896	4.5465 $R_{0.05}$	3.2926
	0.05			
	GARCH	0.0432	3.7689	8.2070
	GARCHTN	0.0511	0.0864	2.8691
	GARCHCN	0.0492	0.0552	2.8187
	GARCHCCN	0.0500	0.0001	2.7810
	0.025			
	GARCH	0.0310	4.9961 $R_{0.025}$	7.6524
	GARCHTN	0.0304	4.1525 $R_{0.025}$	2.6420

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Table I.0.2 – continued from previous page

Data	**p**	x/T	**Kupiec LR test**	$E(shortfall^2)$
	GARCHCN	0.0288	2.0690	2.5868
	GARCHCCN	0.0293	2.6876	2.5274
Danone	0.1			
	GARCH	0.0668	50.5758 $R_{0.01}$	3.2021
	GARCHTN	0.0746	28.5877 $R_{0.01}$	2.0425
	GARCHCN	0.0708	38.3352 $R_{0.01}$	2.0485
	GARCHCCN	0.0955	0.8221	2.0254
	0.05			
	GARCH	0.0429	4.1127 $R_{0.05}$	3.2730
	GARCHTN	0.0396	8.9501 $R_{0.01}$	2.2416
	GARCHCN	0.0385	11.0114 $R_{0.01}$	2.1546
	GARCHCCN	0.0505	0.0185	2.1697
	0.025			
	GARCH	0.0252	0.0090	3.9447
	GARCHTN	0.0247	0.0135	2.3401
	GARCHCN	0.0233	0.4236	2.2781
	GARCHCCN	0.0280	1.2750	2.1839
Gemalto	0.1			
	GARCH	0.0733	19.8845 $R_{0.01}$	5.3255
	GARCHTN	0.0733	19.8845 $R_{0.01}$	4.4714
	GARCHCN	0.0737	19.2102 $R_{0.01}$	4.4427
	GARCHCCN	0.0946	0.7451	4.4032
	0.05			
	GARCH	0.0406	4.5875 $R_{0.025}$	6.2058
	GARCHTN	0.0366	9.4700 $R_{0.01}$	5.6430
	GARCHCN	0.0366	9.4700 $R_{0.01}$	5.6414
	GARCHCCN	0.0545	0.9567	4.7780
	0.025			
	GARCH	0.0257	0.0497	6.8214
	GARCHTN	0.0209	1.6454	6.8840
	GARCHCN	0.0205	2.0302	7.0306
	GARCHCCN	0.0297	1.9259	5.7801
Vallourec	0.1			
	GARCH	0.0733	31.8883 $R_{0.01}$	7.0169
	GARCHTN	0.0774	22.5728 $R_{0.01}$	4.6643
	GARCHCN	0.0757	26.0889 $R_{0.01}$	4.5989
	GARCHCCN	0.0996	0.0059	4.7993
	0.05			
	GARCH	0.0478	0.3898	6.4296
	GARCHTN	0.0423	4.7828 $R_{0.05}$	4.5245

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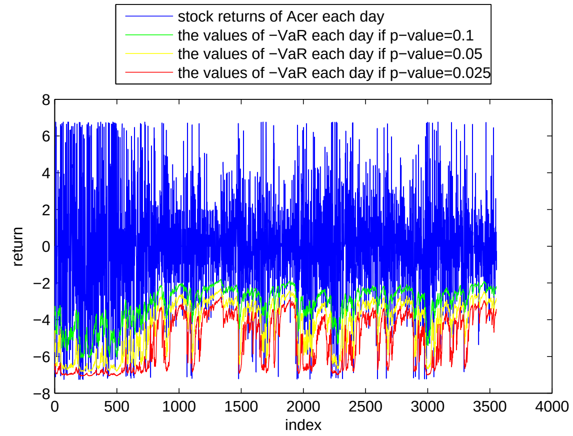
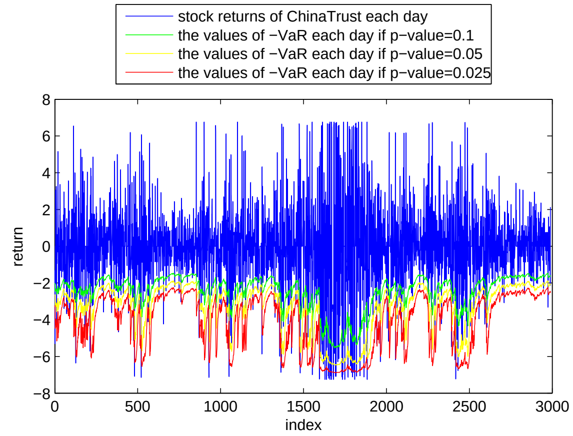
Table I.0.2 – continued from previous page

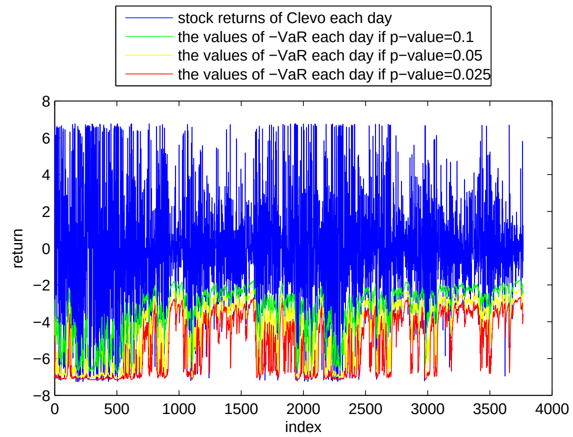
Data	p	x/T	Kupiec LR test	$E(shortfall^2)$
	GARCHCN	0.0402	8.0054 $R_{0.01}$	4.5343
	GARCHCCN	0.0486	0.1559	4.8191
	0.025			
	GARCH	0.0293	2.6698	6.6215
	GARCHTN	0.0261	0.1671	4.2338
	GARCHCN	0.0247	0.0135	4.2222
	GARCHCCN	0.0252	0.0090	4.2999
LVMH	0.1			
	GARCH	0.0825	13.1823 $R_{0.01}$	4.1007
	GARCHTN	0.0874	6.7247 $R_{0.01}$	2.6529
	GARCHCN	0.0817	14.4812 $R_{0.01}$	2.4901
	GARCHCCN	0.0986	0.0851	2.6778
	0.05			
	GARCH	0.0500	0.0001	4.2961
	GARCHTN	0.0475	0.4863	2.7230
	GARCHCN	0.0453	1.7331	2.2749
	GARCHCCN	0.0521	0.3476	2.7200
	0.025			
	GARCH	0.0282	1.5214	5.2579
	GARCHTN	0.0274	0.8606	2.9961
	GARCHCN	0.0255	0.0410	2.2558
	GARCHCCN	0.0296	3.0162	2.6631



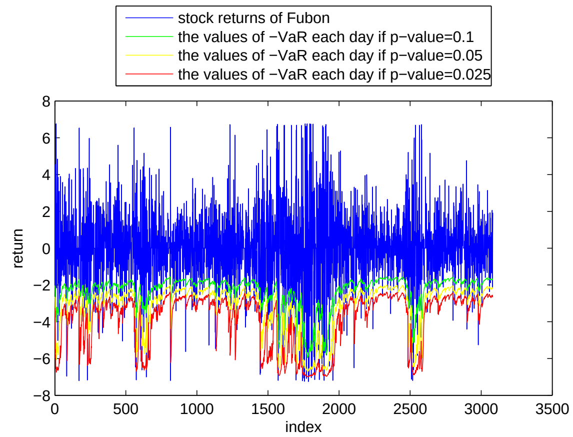
(a) *VaRs of Acer*



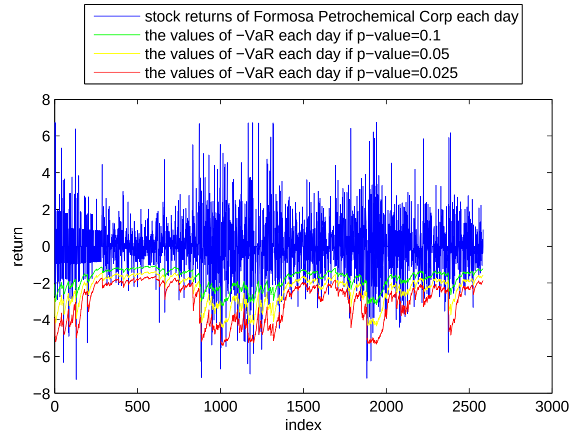
(b) *VaRs of ChinaTrust*



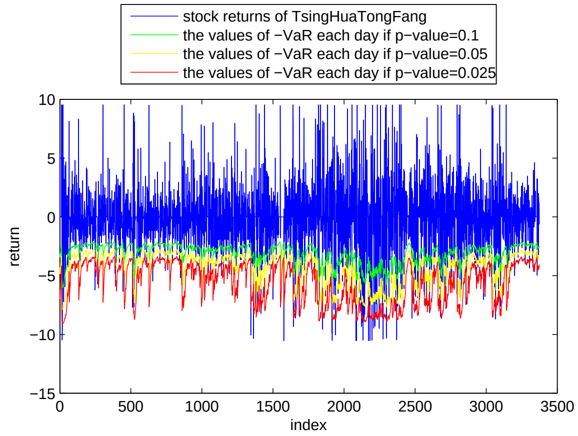
(c) *VaRs of Clevo*



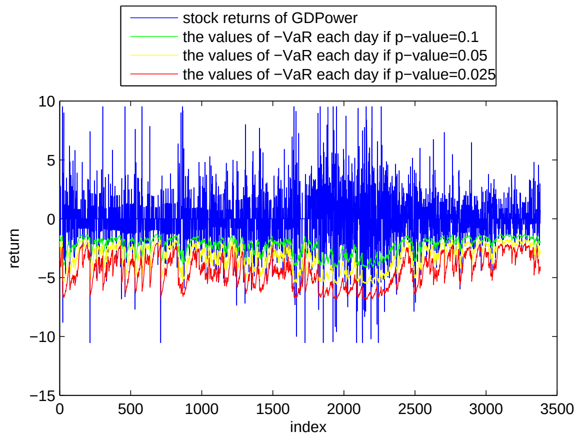
(d) *VaRs of Fubon*



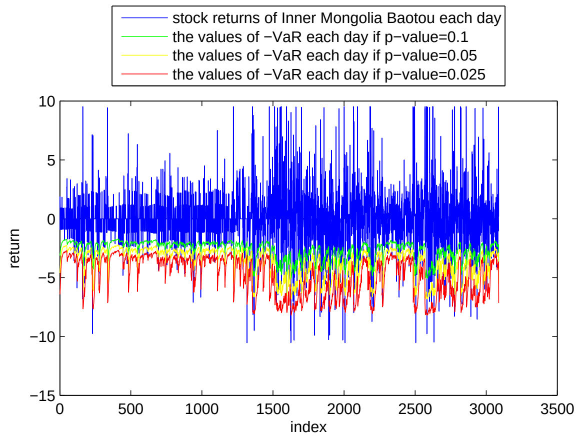
(a) *VaRs of Formosa Petrochemical Corp.*



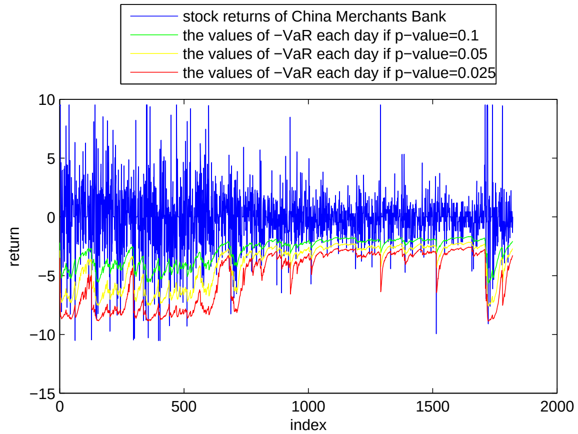
(b) *VaRs of TsingHuaTongFang*



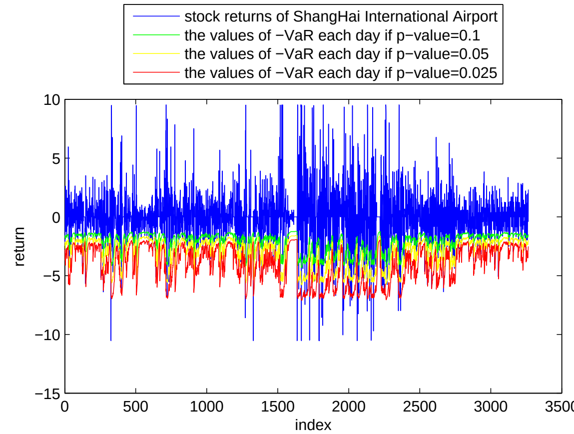
(c) *VaRs of GDPower*



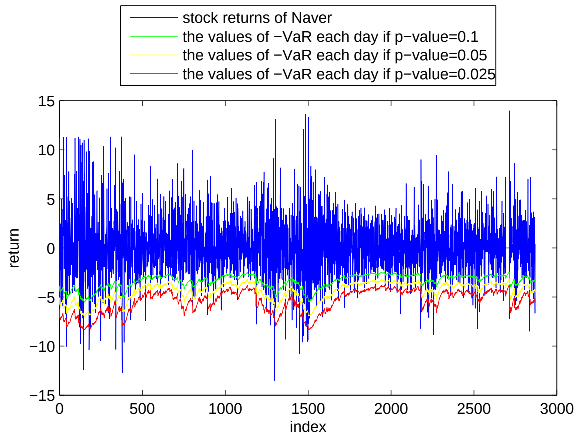
(d) *VaRs of Inner Mongolia Baotou*



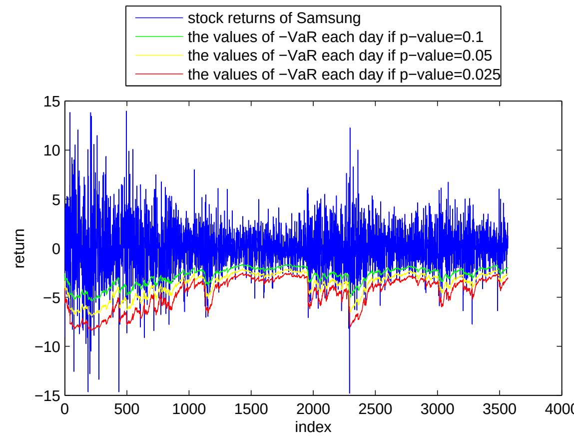
(a) *VaRs of China Merchants Bank*



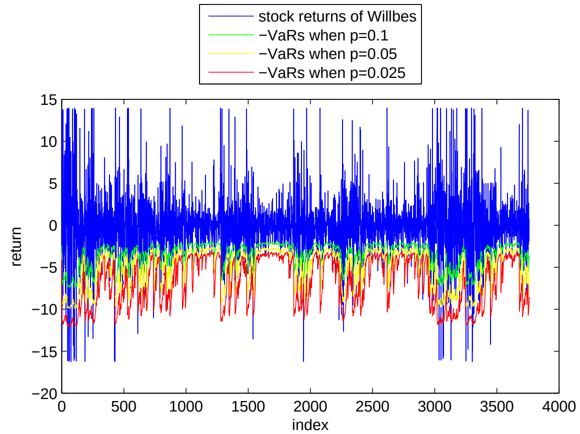
(b) *VaRs of ShangHai International Airport*



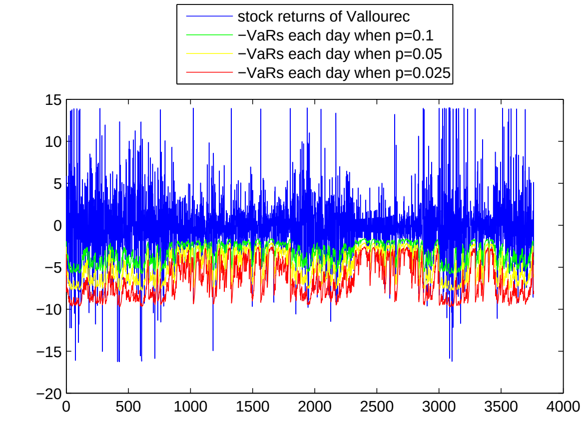
(c) *VaRs of Naver*



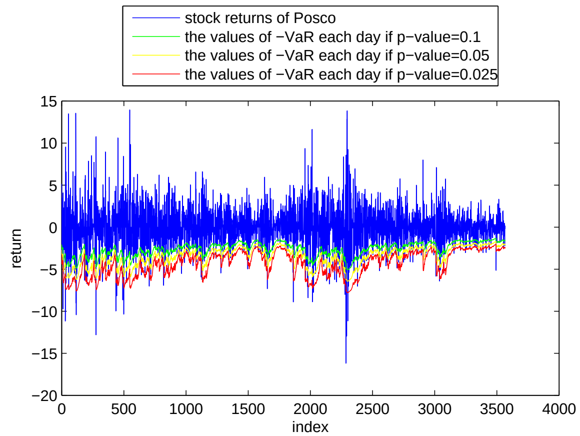
(d) *VaRs of Samsung*



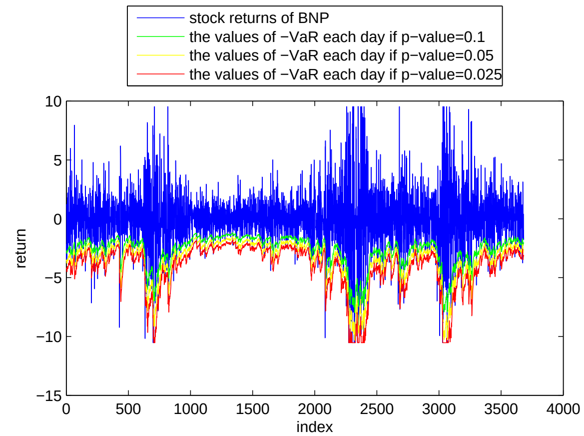
(a) *VaRs of Willbes*



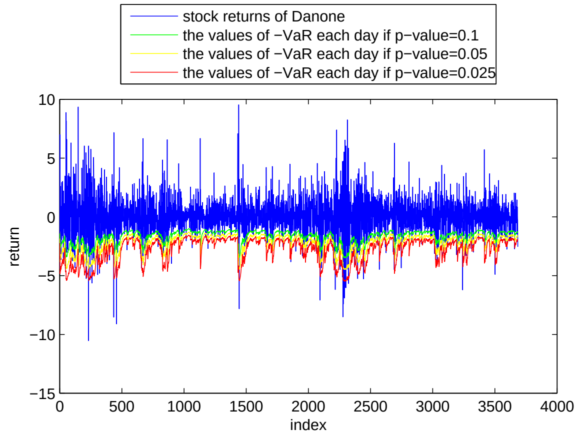
(b) *VaRs of Enex*



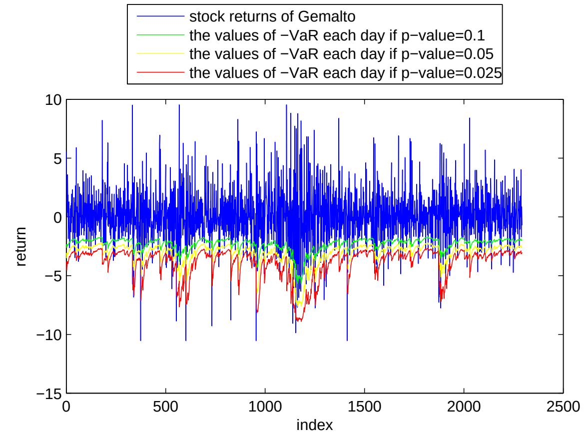
(c) *VaRs of Posco*



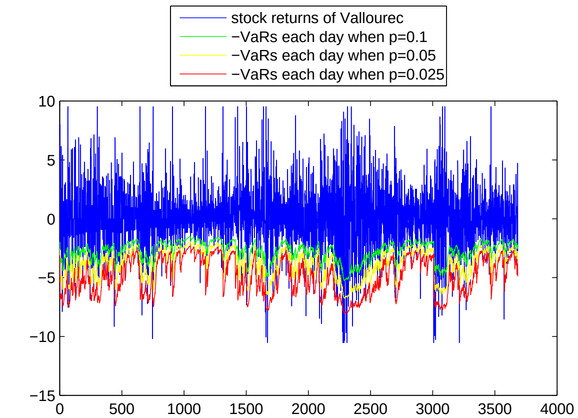
(d) *VaRs of BNP*



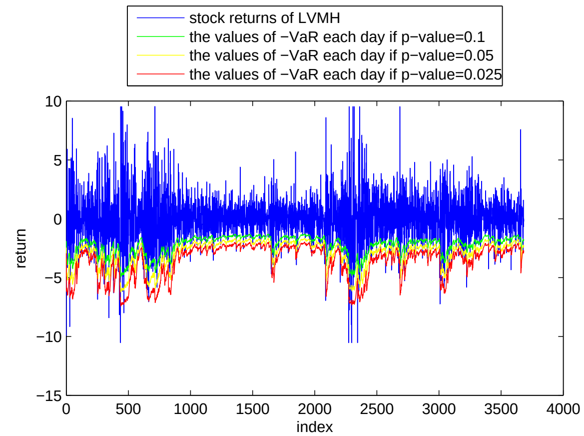
(a) *VaRs of Danone*



(b) *VaRs of Gemalto*



(c) *VaRs of Vallourec*



(d) *VaRs of LVMH*

Appendix J

Moments of CCST

$i \in \{0, 1, 2, 3, 4\}$ in all the following sections.

J.0.7 Moments of a standardized or generalized Student-t with bounds

Let x be a truncated standardized Student-t with degree of freedom of v, the lower bound of $a < 0$, the upper bound of $b > 0$. $cdf_{stdtst}(b; v)$ is the cumulative density function of the standardized Student-t at b; $cdf_{stdtst}(a; v)$ is the cumulative density function of the standardized Student-t at a. These MATLAB functions are in Kevin Sheppard's UCSD_GARCH Toolbox. In order to find the moments of x, a function $betainc(w, c, d,' lower')$ is utilized.

$$\begin{aligned} beta(c, d) &= \int_0^1 t^{c-1}(1-t)^{d-1}\,\mathrm{d}t \\ &= \frac{\Gamma(c)\Gamma(d)}{\Gamma(c+d)} \end{aligned} \tag{J.0.1}$$

$$w \in [0, 1]$$

.

$$betainc(w, c, d, `lower') = \frac{\int_0^w t^{c-1}(1-t)^{d-1}\,\mathrm{d}t}{beta(c, d)} \tag{J.0.2}$$

$$betainc(w, c, d, `upper') = \frac{\int_w^1 t^{c-1}(1-t)^{d-1}\,\mathrm{d}t}{beta(c, d)} \tag{J.0.3}$$

$betainc(w, c, d, `lower')$ and $betainc(w, c, d, `upper')$ are functions ready to be used in MATLAB.

$$Mom_i(a, b; v) = \int_a^b x^i * pdf_{stdtst}(x; v)\,\mathrm{d}x \tag{J.0.4}$$

$$Mom_1(a,b;v) = \frac{\Gamma(\frac{v+1}{2})(v-2)\left[\left(1+\frac{b^2}{v-2}\right)^{1-\frac{v+1}{2}} - \left(1+\frac{a^2}{v-2}\right)^{1-\frac{v+1}{2}}\right]}{2\Gamma(\frac{v}{2})\sqrt{\pi(v-2)}\left(1-\frac{v+1}{2}\right)} \tag{J.0.5}$$

If $a^2 > (v-2)$,

$$Mom_2(-\infty,a;v) = \frac{betainc(\frac{v-2}{v-2+a^2}, \frac{v}{2}-1, 1.5, `lower')}{2} \tag{J.0.6}$$

else,

$$Mom_2(-\infty,a;v) = \frac{betainc(\frac{a^2}{v-2+a^2}, 1.5, \frac{v}{2}-1, `upper')}{2} \tag{J.0.7}$$

If $b^2 > (v-2)$,

$$Mom_2(-\infty,b;v) = 1 - \frac{betainc(\frac{v-2}{v-2+b^2}, \frac{v}{2}-1, 1.5, `lower')}{2} \tag{J.0.8}$$

else,

$$Mom_2(-\infty,b;v) = 1 - \frac{betainc(\frac{b^2}{v-2+b^2}, 1.5, \frac{v}{2}-1, `upper')}{2} \tag{J.0.9}$$

$$Mom_2(a,b;v) = Mom_2(-\infty,b;v) - Mom_2(-\infty,a;v) \tag{J.0.10}$$

If $a^2 > (v-2)$,

$$Mom_3(-\infty,a;v) = \frac{-betainc(\frac{v-2}{v-2+a^2}, \frac{v}{2}-1.5, 2, `lower')beta(\frac{v}{2}-1.5, 2)(v-2)^{1.5}\Gamma(\frac{v+1}{2})}{2\sqrt{\pi}\Gamma(\frac{v}{2})} \tag{J.0.11}$$

else,

$$Mom_3(-\infty,a;v) = \frac{-betainc(\frac{a^2}{v-2+a^2}, 2, \frac{v}{2}-1.5, `upper')beta(\frac{v}{2}-1.5, 2)(v-2)^{1.5}\Gamma(\frac{v+1}{2})}{2\sqrt{\pi}\Gamma(\frac{v}{2})} \tag{J.0.12}$$

If $b^2 > (v-2)$,

$$Mom_3(-\infty,b;v) = -\frac{betainc(\frac{v-2}{v-2+b^2}, \frac{v}{2}-1.5, 2, `lower')beta(\frac{v}{2}-1.5, 2)(v-2)^{1.5}\Gamma(\frac{v+1}{2})}{2\sqrt{\pi}\Gamma(\frac{v}{2})} \tag{J.0.13}$$

else,

$$Mom_3(-\infty, b; v) = -\frac{betainc(\frac{b^2}{v-2+b^2}, 2, \frac{v}{2} - 1.5, \text{`}upper') beta(\frac{v}{2} - 1.5, 2)(v-2)^{1.5}\Gamma(\frac{v+1}{2})}{2\sqrt{\pi}\Gamma(\frac{v}{2})} \tag{J.0.14}$$

$$Mom_3(a, b; v) = Mom_3(-\infty, b; v) - Mom_3(-\infty, a; v) \tag{J.0.15}$$

If $a^2 > (v-2)$,

$$Mom_4(-\infty, a; v) = \frac{betainc(\frac{v-2}{v-2+a^2}, \frac{v}{2} - 2, 2.5, \text{`}lower') beta(\frac{v}{2} - 2, 2.5)(v-2)^2\Gamma(\frac{v+1}{2})}{2\sqrt{\pi}\Gamma(\frac{v}{2})} \tag{J.0.16}$$

else,

$$Mom_4(-\infty, a; v) = \frac{betainc(\frac{a^2}{v-2+a^2}, 2.5, \frac{v}{2} - 2, \text{`}upper') beta(\frac{v}{2} - 2, 2.5)(v-2)^2\Gamma(\frac{v+1}{2})}{2\sqrt{\pi}\Gamma(\frac{v}{2})} \tag{J.0.17}$$

If $b^2 > (v-2)$,

$$Mom_4(-\infty, b; v) = \frac{(2 - betainc(\frac{v-2}{v-2+b^2}, \frac{v}{2} - 2, 2.5, \text{`}lower')) beta(\frac{v}{2} - 2, 2.5)(v-2)^2\Gamma(\frac{v+1}{2})}{2\sqrt{\pi}\Gamma(\frac{v}{2})} \tag{J.0.18}$$

else,

$$Mom_4(-\infty, a; v) = \frac{(2 - betainc(\frac{b^2}{v-2+b^2}, 2.5, \frac{v}{2} - 2, \text{`}upper')) beta(\frac{v}{2} - 2, 2.5)(v-2)^2\Gamma(\frac{v+1}{2})}{2\sqrt{\pi}\Gamma(\frac{v}{2})} \tag{J.0.19}$$

$$Mom_4(a, b; v) = Mom_4(-\infty, b; v) - Mom_4(-\infty, a; v) \tag{J.0.20}$$

Then the moments for generalized Student-t with a location parameter μ, a scale parameter of σ, degree of freedom parameter of v, the lower bound of $Lower$, and the upper bound of $Upper$ is also calculated as follows.

$$Mom_{i_{gt}}(Lower, Upper; \mu, \sigma, v) = \int_{Lower}^{Upper} x^i * pdf_{gt}(x; \mu, \sigma, v)\,\mathrm{d}x \tag{J.0.21}$$

$$\begin{aligned} Mom_{1_{gt}}(Lower, Upper; \mu, \sigma, v) = Mom_1(\frac{Lower-\mu}{\sigma}, \frac{Upper-\mu}{\sigma}; v) * \sigma + \mu(cdf_{stdtst}(\frac{Upper-\mu}{\sigma}; v) \\ - cdf_{stdtst}(\frac{Lower-\mu}{\sigma}; v)) \end{aligned} \tag{J.0.22}$$

$$Mom_{2_{gt}}(Lower, Upper; \mu, \sigma, v) = Mom_2(\frac{Lower - \mu}{\sigma}, \frac{Upper - \mu}{\sigma}; v) * \sigma^2$$
$$+ 2\sigma\mu Mom_1(\frac{Lower - \mu}{\sigma}, \frac{Upper - \mu}{\sigma}; v) \quad (J.0.23)$$
$$+ \mu^2(cdf_{stdtst}(\frac{Upper - \mu}{\sigma}; v) - cdf_{stdtst}(\frac{Lower - \mu}{\sigma}; v))$$

$$Mom_{3_{gt}}(Lower, Upper; \mu, \sigma, v) = Mom_3(\frac{Lower - \mu}{\sigma}, \frac{Upper - \mu}{\sigma}; v) * \sigma^3$$
$$+ 3\sigma^2\mu Mom_2(\frac{Lower - \mu}{\sigma}, \frac{Upper - \mu}{\sigma}; v)$$
$$+ 3\sigma\mu^2 Mom_1(\frac{Lower - \mu}{\sigma}, \frac{Upper - \mu}{\sigma}; v) + \mu^3(cdf_{stdtst}(\frac{Upper - \mu}{\sigma}; v)$$
$$- cdf_{stdtst}(\frac{Lower - \mu}{\sigma}; v))$$
$$(J.0.24)$$

$$Mom_{4_{gt}}(Lower, Upper; \mu, \sigma, v) = Mom_4(\frac{Lower - \mu}{\sigma}, \frac{Upper - \mu}{\sigma}; v) * \sigma^4$$
$$+ 4\sigma^3\mu Mom_3(\frac{Lower - \mu}{\sigma}, \frac{Upper - \mu}{\sigma}; v)$$
$$+ 6\sigma^2\mu^2 Mom_2(\frac{Lower - \mu}{\sigma}, \frac{Upper - \mu}{\sigma}; v) \quad (J.0.25)$$
$$+ 4\sigma\mu^3 Mom_1(\frac{Lower - \mu}{\sigma}, \frac{Upper - \mu}{\sigma}; v)$$
$$(cdf_{stdtst}(\frac{Upper - \mu}{\sigma}; v) - cdf_{stdtst}(\frac{Lower - \mu}{\sigma}; v))$$

J.0.8 Clustered Censored generalized Student-t

$A = pdf_{gt}(a_1; \mu, \sigma, v)$ and $B = pdf_{gt}(b_1; \mu, \sigma, v)$. All the other variables in this section are granted the same meanings as in section 3.2.1. Let $y \in [a_1, b_1]$,

$$M_{i_{ccgt}}(y, parameters, Lower, Upper) = Mom_{i_{gt}}(a_1, y; \mu, \sigma, v) \quad (J.0.26)$$

$$M_{i_{ccgt}}(parameters, Lower, Upper) = Mom_{i_{gt}}(a_1, b_1; \mu, \sigma, v) \quad (J.0.27)$$

Let $y \in [Lower, a_1]$, if $m_1 \neq 0$,

$$L_{i_{ccgt}}(y, parameters, Lower, Upper) = \int_{Lower}^{y} x^i * A * exp(m_1 * (x - a_1))dx$$
$$= \frac{A}{m_1}[y^i - Lower^i * exp(m_1 * (Lower - a_1))] - iL_{i-1_{ccgt}}(y,$$
$$parameters, Lower, Upper)/m_1$$
$$(J.0.28)$$

$$L_{i_{ccgt}}(parameters, Lower, Upper) = L_{i_{ccgt}}(a_1, parameters, Lower, Upper) \quad (J.0.29)$$

$$L_{0_{ccgt}}(y, parameters, Lower, Upper) = \frac{A}{m_1}\left[exp(m_1(y - a_1)) - exp(m_1(Lower - a_1))\right] \quad (J.0.30)$$

$$L_{0_{ccgt}}(parameters, Lower, Upper) = \frac{A}{m_1}\left[1 - exp(m_1(Lower - a_1))\right] \quad (J.0.31)$$

$$L_{i_{ccgt}}(parameters, Lower, Upper) = \frac{A}{m_1}[a_1^i - Lower^i * exp(m_1 * (Lower - a_1))] - iL_{i-1_{ccgt}}(parameters, Lower, Upper)/m_1 \quad (J.0.32)$$

If $m_1 = 0$,

$$L_{i_{ccgt}}(y, parameters, Lower, Upper) = A\frac{y^{i+1} - Lower^{i+1}}{i+1} \quad (J.0.33)$$

$$L_{i_{ccgt}}(parameters, Lower, Upper) = L_{i_{ccgt}}(a_1, parameters, Lower, Upper) = A\frac{a_1^{i+1} - Lower^{i+1}}{i+1} \quad (J.0.34)$$

Let $y \in [b_1, Upper]$, if $m_2 \neq 0$,

$$R_{0_{ccgt}}(y, parameters, Lower, Upper) = \frac{B}{m_2}\left[exp(m_2(y - b_1)) - 1\right] \quad (J.0.35)$$

$$R_{0_{ccgt}}(U, parameters, Lower, Upper) = \frac{B}{m_2}\left[exp(m_2(Upper - b_1)) - 1\right] \quad (J.0.36)$$

$$\begin{aligned} R_{i_{ccgt}}(y, parameters, Lower, Upper) &= \int_{b_1}^{y} x^i * B * exp(m_2 * (x - b_1))dx \\ &= \frac{B}{m_2}[y^i * exp(m_2 * (y - b_1) - {b_1}^i)] \\ &- i * R_{i-1_{ccgt}}(y, parameters, Lower, Upper)/m_2 \end{aligned} \quad (J.0.37)$$

$$R_{i_{ccgt}}(parameters, Lower, Upper) = R_{i_{ccgt}}(Upper, parameters, Lower, Upper) \quad (J.0.38)$$

If $m_2 = 0$,

$$R_{i_{ccgt}}(y, parameters, Lower, Upper) = B\frac{y^{i+1} - b_1^{i+1}}{i+1} \quad (J.0.39)$$

$$R_{i_{ccgt}}(parameters, Lower, Upper) = R_{i_{ccgt}}(Upper, parameters, Lower, Upper)) = B\frac{Upper^{i+1} - b_1^{i+1}}{i+1} \quad (J.0.40)$$

Suppose x follows clustered censored Student-t distribution with a location parameter of μ, a scale parameter of σ, a degree of freedom of v, left and right clustering rates of l_1 and r_1, left and right clustering coefficients of m_1 and m_2, lower bound of $Lower$, and upper bound of $Upper$.

Let $parameters = (\mu; \sigma; v; l_1; r_1; m_1; m_2)$.

$$E(x^i) = [R_{i_{ccgt}}(parameters, Lower, Upper) + L_{i_{ccgt}}(parameters, Lower, Upper) + Mom_{i_{gt}}(a_1, b_1; \mu, \sigma, v)]/\Omega_{ccgt} \tag{J.0.41}$$

$$E(x) = mean_{ccgt}(parameters, Lower, Upper) \tag{J.0.42}$$

Equation J.0.22 is used for the value of $Mom_{1_{gt}}(a_1, b_1; \mu, \sigma, v)$.

$$E(x^2) = secondmoment_{ccgt}(parameters, Lower, Upper) \tag{J.0.43}$$

Equation J.0.23 is used for the value of $Mom_{2_{gt}}(a_1, b_1; \mu, \sigma, v)$.

$$\begin{aligned} variance(x) &= variance_{ccgt}(parameters, Lower, Upper) \\ &= secondmoment_{ccgt}(parameters, Lower, Upper) - mean_{ccgt}(parameters, Lower, Upper)^2 \end{aligned} \tag{J.0.44}$$

$$E(x^3) = thirdmoment_{ccgt}(parameters, Lower, Upper) \tag{J.0.45}$$

Equation J.0.24 is used for the value of $Mom_{3_{gt}}(a_1, b_1; \mu, \sigma, v)$.

$$\begin{aligned} skewness_{ccgt}(parameters, Lower, Upper)) &= E\left(\frac{(x - mean(x))^3}{variance_{ccgt}(parameters, Lower, Upper))^{\frac{3}{2}}}\right) \\ &= \frac{E(x^3) + 2 * (E(x))^3 + 3 * E(x^2) * E(x)}{variance(x)^{\frac{3}{2}}} \end{aligned} \tag{J.0.46}$$

This skewness values of x can be found by using equation J.0.45, J.0.43, and J.0.42.

$$E(x^4) = fourthmoment_{ccgt}(parameters, Lower, Upper)) \tag{J.0.47}$$

Equation J.0.25 is used for the value of $Mom_{4_{gt}}(a_1, b_1; \mu, \sigma, v)$.

$$\begin{aligned} kurtosis_{ccgt}(parameters, Lower, Upper)) &= kurtosis(x) \\ &= E\left(\frac{(x - mean(x))^4}{variance(x)^2}\right) \\ &= \frac{E(x^4) + 6(E(x)(^2E(x^2) - 4E(x)E(x^3) - 3(E(x))^4}{variance(x)^2} \end{aligned} \tag{J.0.48}$$

This kurtosis value can be attained by using equation J.0.47, J.0.45, J.0.43, and J.0.42

Appendix K

Moments of CCGED

Likewise, let $v > 0$. If x is a random variable of a standardized GED with a degree of freedom of v, the pdf of x can be obtained by

$$Beta = \left(2^{-\frac{2}{v}} \frac{\Gamma(\frac{1}{v})}{\Gamma(\frac{3}{v})}\right)^{0.5} \tag{K.0.1}$$

$$pdf_{stdtged}(x; v) = \frac{v2^{-(1+\frac{1}{v})}}{Beta\Gamma(\frac{1}{v})exp\left[-0.5 \mid \frac{y}{Beta} \mid^{v}\right]} \tag{K.0.2}$$

If x follows GED with a location parameter of μ, a scale parameter of σ, and degree of freedom of v, the pdf of x is given by

$$\begin{aligned} pdf_{ged}(x; \mu, \sigma, v) &= \frac{v2^{-(1+\frac{1}{v})}}{\sigma Beta\Gamma(\frac{1}{v})exp\left[-0.5 \mid \frac{x-\mu}{Beta*\sigma} \mid^{v}\right]} \\ &= \frac{pdf_{stdged}(\frac{x-\mu}{\sigma}; v)}{\sigma} \end{aligned} \tag{K.0.3}$$

The *pdf* of a clustered censored generalized GED consist of three sections. Let $parameters = (\mu; \sigma^2; v; l_1; r_1; m_1; m_2)$. *Lower* is the lower bound and *Upper* is the upper bound. Let $a_1 = \mu + l_1 * (Lower - \mu)$ and $b_1 = \mu + r_1 * (Upper - \mu)$. $A = pdf_{ged}(a_1; \mu, \sigma, v)$ and $B = pdf_{ged}(b_1; \mu, \sigma, v)$.

$$M_{0_{ccged}}(parameters, Lower, Upper) = cdf_{stdtged}(\frac{b_1 - \mu}{\sigma}; \nu) - cdf_{stdtged}(\frac{a_1 - \mu}{\sigma}; \nu) \tag{K.0.4}$$

Using equations K.0.20, K.0.25, K.0.22, K.0.27, and K.0.4, the following formula is defined,

$$\begin{aligned} \Omega_{ccged}(parameters, Lower, Upper) = {} & L_{0_{ccged}}(parameters, Lower, Upper) \\ & + M_{0_{ccged}}(parameters, Lower, Upper) \\ & + R_{0_{ccged}}(parameters, Lower, Upper) \end{aligned} \tag{K.0.5}$$

Therefore, the *pdf* and *cdf* (Notes: $pdf_{ccged}(x, parameters, Lower, Upper)$, $cdf_{ccged}(x, parameters, Lower, Upper)$, $L0_{ccged}(parameters, Lower, Upper)$, $M0_{ccged}(parameters, Lower, Upper)$, and $R0_{ccged}(parameters, Lower, Upper)$ are shortened as $pdf_{ccged}(x)$, $cdf_{ccged}(x)$, $L0_{ccged}$, $M0_{ccged}$, and $R0_{ccged}$ in definition of *pdf* and *cdf* below) are given by,

$$pdf_{ccged}(x) = \begin{cases} \frac{pdf_{ged}(x;\mu,\sigma,v)}{\Omega_{ccged}(parameters,Lower,Upper)} & \text{if } a_1 \leq x \leq b_1 \\ \frac{exp(m_1(x-a_1))A}{\Omega_{ccged}(parameters,Lower,Upper)} & \text{if } Lower \leq x \leq a_1 \\ \frac{exp(m_2(x-b_1))B}{\Omega_{ccged}(parameters,Lower,Upper)} & \text{if } b_1 \leq x \leq Upper \\ 0 & \text{else} \end{cases}$$

$$cdf_{ccged}(x) = \left\{ \begin{array}{ll} 0 & \text{if } x < Lower \\ \frac{L0_{ccged}(x,parameters,Lower,Upper)}{\Omega_{ccged}(parameters,Lower,Upper)} & \text{if } Lower \leq x \leq a_1 \\ \frac{L0_{ccged}+M0_{ccged}(x,parameters,Lower,Upper)}{\Omega_{ccged}(parameters,Lower,Upper)} & \text{if } a_1 \leq x \leq b_1 \\ \frac{L0_{ccged}+M0_{ccged}+R0_{ccged}(x,parameters,Lower,Upper)}{\Omega_{ccged}(parameters,Lower,Upper)} & \text{if } b_1 \leq x \leq Upper \\ 1 & \text{if } x > Upper \end{array} \right\}$$

The mean, variance, skewness, and kurtosie of x with a clustered censored GED are derived in equations K.0.29, K.0.31, K.0.33, and K.0.35.

$i \in \{0, 1, 2, 3, 4\}$.

K.0.9 The moments of standardized or generalized GED with bounds

Let x be a truncated standardized GED with degree of freedom of v, the lower bound of $a < 0$, the upper bound of $b > 0$. $cdf_{stdtged}(b; v)$ is the cumulative density function of the standardized GED at b; $cdf_{stdtged}(a; v)$ is the cumulative density function of the standardized GED at a. These MATLAB functions are in Kevin Sheppard's UCSD_GARCH Toolbox.

In order to calculate the moments of x, a MATLAB function, $gamcdf(x, m, n)$, is used. m, $n \in \mathbb{R}$

$$gamcdf(x, m, n) = \frac{1}{n^m \Gamma(m)} \int_0^x t^{m-1} exp(-\frac{t}{n}) dt \tag{K.0.6}$$

If $n = 1$, a $gamcdf(x, m)$ is equal to $gamcdf(x, m, n)$. Consequently,

$$gamcdf(x, m) = \frac{1}{\Gamma(m)} \int_0^x t^{m-1} exp(-t) dt \tag{K.0.7}$$

$$Mom_{i_{stdtged}}(a,b;v) = \int_a^b x^i * pdf_{stdtged}(x;v)\,\mathrm{d}x \tag{K.0.8}$$

$$Mom_{1_{stdtged}}(a,b;v) = \sqrt{\frac{\Gamma(\frac{1}{v})}{\Gamma(\frac{3}{v})}}\frac{\Gamma(\frac{2}{v})}{2\Gamma(\frac{1}{v})}\left[gamcdf\left(\left[\frac{\Gamma(\frac{3}{v})}{\Gamma(\frac{1}{v})}b^2\right]^{\frac{v}{2}},\frac{2}{v}\right) - gamcdf\left(\left[\frac{\Gamma(\frac{3}{v})}{\Gamma(\frac{1}{v})}a^2\right]^{\frac{v}{2}},\frac{2}{v}\right)\right] \tag{K.0.9}$$

$$Mom_{2_{stdtged}}(a,b;v) = 0.5gamcdf\left(\left[\frac{\Gamma(\frac{3}{v})}{\Gamma(\frac{1}{v})}b^2\right]^{\frac{v}{2}},\frac{3}{v}\right) + 0.5gamcdf\left(\left[\frac{\Gamma(\frac{3}{v})}{\Gamma(\frac{1}{v})}a^2\right]^{\frac{v}{2}},\frac{3}{v}\right) \tag{K.0.10}$$

$$Mom_{3_{stdtged}}(a,b;v) = 0.5\frac{\Gamma(\frac{4}{v})}{\Gamma(\frac{1}{v})}\left(\sqrt{\frac{\Gamma(\frac{1}{v})}{\Gamma(\frac{3}{v})}}\right)^3\left(gamcdf\left(\left[\frac{\Gamma(\frac{3}{v})}{\Gamma(\frac{1}{v})}b^2\right]^{\frac{v}{2}},\frac{4}{v}\right) - gamcdf\left(\left[\frac{\Gamma(\frac{3}{v})}{\Gamma(\frac{1}{v})}a^2\right]^{\frac{v}{2}},\frac{4}{v}\right)\right) \tag{K.0.11}$$

$$Mom_{4_{stdtged}}(a,b;v) = 0.5\frac{\Gamma(\frac{5}{v})}{\Gamma(\frac{1}{v})}\left(\frac{\Gamma(\frac{1}{v})}{\Gamma(\frac{3}{v})}\right)^2\left(gamcdf\left(\left[\frac{\Gamma(\frac{3}{v})}{\Gamma(\frac{1}{v})}b^2\right]^{\frac{v}{2}},\frac{5}{v}\right) + gamcdf\left(\left[\frac{\Gamma(\frac{3}{v})}{\Gamma(\frac{1}{v})}a^2\right]^{\frac{v}{2}},\frac{5}{v}\right)\right) \tag{K.0.12}$$

Then the moments for generalized Student-t with a location parameter μ, a scale parameter parameter of σ, degree of freedom parameter of v, the lower bound of $Lower$, and the upper bound of $Upper$ is also shown as follows.

$$Mom_{i_{ged}}(Lower,Upper;\mu,\sigma,v) = \int_{Lower}^{Upper} x^i * pdf_{ged}(x;\mu,\sigma,v)\,\mathrm{d}x \tag{K.0.13}$$

$$\begin{aligned} Mom_{1_{ged}}(Lower,Upper;\mu,\sigma,v) = {} & Mom_{1_{stdtged}}(\frac{Lower-\mu}{\sigma},\frac{Upper-\mu}{\sigma};v)*\sigma \\ & + \mu(cdf_{stdtged}(\frac{Upper-\mu}{\sigma};v) - cdf_{stdtged}(\frac{Lower-\mu}{\sigma};v)) \end{aligned} \tag{K.0.14}$$

$$\begin{aligned} Mom_{2_{ged}}(Lower,Upper;\mu,\sigma,v) = {} & Mom_{2_{stdtged}}(\frac{Lower-\mu}{\sigma},\frac{Upper-\mu}{\sigma};v)*\sigma^2 \\ & + 2\sigma\mu Mom_{1_{stdtged}}(\frac{Lower-\mu}{\sigma},\frac{Upper-\mu}{\sigma};v) \\ & + \mu^2(cdf_{stdtged}(\frac{Upper-\mu}{\sigma};v) - cdf_{stdtged}(\frac{Lower-\mu}{\sigma};v)) \end{aligned} \tag{K.0.15}$$

$$
\begin{aligned}
Mom_{3_{ged}}(Lower, Upper; \mu, \sigma, v) = {} & Mom_{3_{stdtged}}(\frac{Lower-\mu}{\sigma}, \frac{Upper-\mu}{\sigma}; v) * \sigma^3 \\
& + 3\sigma^2 \mu Mom_{2_{stdtged}}(\frac{Lower-\mu}{\sigma}, \frac{Upper-\mu}{\sigma}; v) \\
& + 3\sigma\mu^2 Mom_{1_{stdtged}}(\frac{Lower-\mu}{\sigma}, \frac{Upper-\mu}{\sigma}; v) \\
& + \mu^3(cdf_{stdtged}(\frac{Upper-\mu}{\sigma}; v) - cdf_{stdtged}(\frac{Lower-\mu}{\sigma}; v))
\end{aligned}
\tag{K.0.16}
$$

$$
\begin{aligned}
& Mom_{4_{ged}}(Lower, Upper; \mu, \sigma, v) \\
& = Mom_{4_{stdtged}}(\frac{Lower-\mu}{\sigma}, \frac{Upper-\mu}{\sigma}; v) * \sigma^4 + 4\sigma^3 \mu Mom_{3_{stdtged}}(\frac{Lower-\mu}{\sigma}, \frac{Upper-\mu}{\sigma}; v) \\
& \quad + 6\sigma^2\mu^2 Mom_{2_{stdtged}}(\frac{Lower-\mu}{\sigma}, \frac{Upper-\mu}{\sigma}; v) \\
& \quad + 4\sigma\mu^3 Mom_{1_{stdtged}}(\frac{Lower-\mu}{\sigma}, \frac{Upper-\mu}{\sigma}; v)(cdf_{stdtged}(\frac{Upper-\mu}{\sigma}; v) \\
& \qquad - cdf_{stdtged}(\frac{Lower-\mu}{\sigma}; v))
\end{aligned}
\tag{K.0.17}
$$

K.0.10 Clustered Censored GED

$A = pdf_{ged}(a_1; \mu, \sigma, v)$ and $B = pdf_{ged}(b_1; \mu, \sigma, v)$. All the other variables in this section are granted the same meanings as in section 3.2.2.

Let $y \in [Lower, a_1]$, if $m_1 \neq 0$,

$$
\begin{aligned}
L_{0_{ccged}}(y, parameters, Lower, Upper) &= \int_{Lower}^{y} A * exp(m_1 * (x - a_1))dx \\
&= \frac{A}{m_1}[exp(m_1 * (y - a_1)) - exp(m_1 * (Lower - a_1))]
\end{aligned}
\tag{K.0.18}
$$

Then for $i = 1, 2, 3, 4$,

$$
\begin{aligned}
L_{i_{ccged}}(y, parameters, Lower, Upper) &= \int_{Lower}^{y} x^i * A * exp(m_1 * (x - a_1))dx \\
&= \frac{A}{m_1}[y^i * exp(m_1 * (y - a_1)) - Lower^i * exp(m_1 * (Lower - a_1))] \\
&\quad - i * L_{i-1_{ccged}}(y, parameters, Lower, Upper)/m_1
\end{aligned}
\tag{K.0.19}
$$

$$L_{i_{ccged}}(parameters, Lower, Upper) = \int_{Lower}^{a_1} x^i * A * exp(m_1 * (x - a_1))dx$$
$$= \frac{A}{m_1}[{a_1}^i - Lower^i * exp(m_1 * (Lower - a_1))] \quad \text{(K.0.20)}$$
$$- i * L_{i-1_{ccged}}(parameters, Lower, Upper)/m_1$$

If $m_1 = 0$,

$$L_{i_{ccged}}(y, parameters, Lower, Upper) = A\frac{y^{i+1} - Lower^{i+1}}{i+1} \quad \text{(K.0.21)}$$

$$L_{i_{ccged}}(parameters, Lower, Upper) = L_{i_{ccged}}(a_1, parameters, Lower, Upper) = A\frac{a_1^{i+1} - Lower^{i+1}}{i+1} \quad \text{(K.0.22)}$$

Let $y \in [b_1, Upper]$, if $m_2 \neq 0$,

$$R_{0_{ccged}}(y, parameters, Lower, Upper) = \int_{b_1}^{y} B * exp(m_2 * (x - b_1))dx$$
$$= \frac{B}{m_2}[exp(m_2 * (y - b_1)) - 1] \quad \text{(K.0.23)}$$

Then for $i = 1, 2, 3, 4$,

$$R_{i_{ccged}}(y, parameters, Lower, Upper) = \int_{b_1}^{y} x^i * B * exp(m_2 * (x - b_1))dx$$
$$= \frac{B}{m_2}[y^i * exp(m_2 * (y - b_1)) - b_1^i)]$$
$$- i * R_{i-1_{ccged}}(y, parameters, Lower, Upper)/m_2 \quad \text{(K.0.24)}$$

$$R_{i_{ccged}}(parameters, Lower, Upper) = \int_{b_1}^{Upper} x^i * B * exp(m_2 * (x - b_1))dx$$
$$= \frac{B}{m_2}[Upper^i * exp(m_2 * (Upper - b_1)) - b_1^i)] \quad \text{(K.0.25)}$$
$$- i * R_{i-1_{ccged}}(parameters, Lower, Upper)/m_2$$

If $m_2 = 0$,

$$R_{i_{ccged}}(y, parameters, Lower, Upper) = B\frac{y^{i+1} - b_1^{i+1}}{i+1} \quad \text{(K.0.26)}$$

$$R_{i_{ccged}}(parameters, Lower, Upper) = R_{i_{ccged}}(Upper, parameters, Lower, Upper) = B\frac{Upper^{i+1} - b_1^{i+1}}{i+1} \quad \text{(K.0.27)}$$

Suppose x follows clustered censored student-t distribution with a location parameter of μ, a scale parameter of σ, a degree of freedom of v, left and right clustering rates of l_1 and r_1, left and right clustering coefficients of m_1 and m_2, lower bound of $Lower$, and upper bound of $Upper$.

Let $parameters = (\mu; \sigma; v; l_1; r_1; m_1; m_2)$.

$$E(x^i) = [R_{i_{ccged}}(parameters, Lower, Upper) + L_{i_{ccged}}(parameters, Lower, Upper) + Mom_{i_{gt}}(a_1, b_1; \mu, \sigma, v)]/\Omega_{ccged} \tag{K.0.28}$$

$$E(x) = mean_{ccged}(parameters, Lower, Upper) \tag{K.0.29}$$

Equation K.0.14 is used for the value of $Mom_{1_{ged}}(a_1, b_1; \mu, \sigma, v)$.

$$E(x^2) = secondmoment_{ccged}(parameters, Lower, Upper) \tag{K.0.30}$$

Equation K.0.15 is used for the value of $Mom_{2_{ged}}(a_1, b_1; \mu, \sigma, v)$.

$$\begin{aligned} variance(x) &= variance_{ccged}(parameters, Lower, Upper) \\ &= secondmoment_{ccged}(parameters, Lower, Upper) - mean_{ccged}(parameters, \\ &Lower, Upper)^2 \end{aligned} \tag{K.0.31}$$

Let $\sigma^* = \sqrt{variance(x)}$.

$$E(x^3) = thirdmoment_{ccged}(parameters, Lower, Upper) \tag{K.0.32}$$

Equation K.0.16 is used for the value of $Mom_{3_{ged}}(a_1, b_1; \mu, \sigma, v)$.

$$\begin{aligned} skewness_{ccged}(parameters, Lower, Upper) &= E\left(\frac{(x - mean(x))^3}{variance_{ccged}(parameters, Lower, Upper)^{\frac{3}{2}}}\right) \\ &= \frac{E(x^3) + 2 * (E(x))^3 + 3 * E(x^2) * E(x)}{\sigma^{*3}} \end{aligned} \tag{K.0.33}$$

This skewness values of x can be found by using equation K.0.32, K.0.30, and K.0.29.

$$E(x^4) = fourthmoment_{ccged}(parameters, Lower, Upper) \tag{K.0.34}$$

Equation K.0.17 is used for the value of $Mom_{4_{ged}}(a_1, b_1; \mu, \sigma, v)$.

$$\begin{aligned} kurtosis_{ccged}(parameters, Lower, Upper) &= kurtosis(x) \\ &= E\left(\frac{(x - mean(x))^4}{variance(x)^2}\right) \\ &= \frac{E(x^4) + 6(E(x))^2 E(x^2) - 4E(x)E(x^3) - 3(E(x))^4}{\sigma^{*4}} \end{aligned} \tag{K.0.35}$$

This kurtosis value can be attained by using equation K.0.34, K.0.32, K.0.30, and K.0.29

Appendix L

Out-of-sample VaRs of Seven Stocks

Table L.0.1: Out-of-sample VaR test statistics when $T_0 = 400$

Data	**p**	x/T	**Kupiec LR test**	$E(shortfall^2)$	LR_{cc}
ChinaTrust	0.1				
	$GARCHST$	0.0725	3.6809(0.1)	0.9329	4.4988(0.1)
	$GARCHCCST$	0.0875	0.7219	0.8583	0.7239
	$GARCHCCST_p$	0.0900	0.4583	0.8291	0.4817
	0.05				
	$GARCHST$	0.0850	1.0482	0.8074	1.0525
	$GARCHCCST$	0.0400	0.9014	0.3128	2.2386
	$GARCHCCST_p$	0.0400	0.9014	0.3024	2.2386
	0.025				
	$GARCHST$	0.0325	3.8036(0.1)	2.0942	2.0942
	$GARCHCCST$	0.0150	1.9110	0.1132	2.0942
	$GARCHCCST_p$	0.0150	1.9110	0.1073	2.0942
Clevo	0.1				
	$GARCHST$	0.0600	8.1812(0.005)	3.0792	11.2553 (0.005)
	$GARCHCCST$	0.0700	4.4218(0.05)	2.9282	8.6523(0.025)
	$GARCHCCST_p$	0.0700	4.4218(0.05)	2.9261	8.6523 (0.025)
	0.05				
	$GARCHST$	0.0300	3.9074(0.05)	1.8640	4.6517(0.1)
	$GARCHCCST$	0.0325	2.9278 (0.1)	1.7298	3.8036
	$GARCHCCST_p$	0.0325	2.9278(0.1)	1.7269	3.8036
	0.025				
	$GARCHST$	0.0125	3.1324(0.1)	1.1893	3.2593
	$GARCHCCST$	0.0125	3.1324(0.1)	1.0414	3.2593
	$GARCHCCST_p$	0.0125	3.1324(0.1)	1.0400	3.2593
Fubon	0.1				
	$GARCHST$	0.0800	1.8953	1.4504	2.0533
	$GARCHCCST$	0.0800	1.8953	1.4558	1.9781
	$GARCHCCST_p$	0.0800	1.8953	1.4571	1.9781
	0.05				
	$GARCHST$	0.0400	0.9014	0.6346	1.0893
	$GARCHCCST$	0.0400	0.9014	0.6242	1.0893
	$GARCHCCST_p$	0.0400	0.9014	0.6233	1.0893
	0.025				
	$GARCHST$	0.0225	0.1061	0.2440	0.5215
	$GARCHCCST$	0.0225	0.1061	0.2253	0.5215
	$GARCHCCST_p$	0.0200	0.4399	0.2248	0.7673

Continued on next page

Table L.0.1 – continued from previous page

Data	p	x/T	Kupiec LR test	$E(shortfall^2)$	LR_{cc}
GDPower	0.1				
	$GARCHST$	0.0725	3.6809 (0.1)	0.9329	4.4988 (0.1)
	$GARCHCCST$	0.0875	0.7219	0.9634	1.0360
	$GARCHCCST_p$	0.0875	0.7219	0.9640	1.0360
	0.05				
	$GARCHST$	0.0250	6.3979 (0.025)	0.3093	7.7865(0.025)
	$GARCHCCST$	0.0325	2.9278(0.1)	0.4225	3.8036
	$GARCHCCST_p$	0.0325	2.9278 (0.1)	0.4221	3.8036
	0.025				
	$GARCHST$	0.0100	4.7615(0.05)	0.0438	4.8425(0.1)
	$GARCHCCST$	0.0200	0.4399	0.1261	0.7673
	$GARCHCCST_p$	0.0200	0.4399	0.1256	0.7673
Lotes	0.1				
	$GARCHST$	0.0550	10.5805 (0.005)	1.0906	11.0688 (0.005)
	$GARCHCCST$	0.0875	0.7219	0.9634	1.0360
	$GARCHCCST_p$	0.0875	0.7219	0.9640	1.0360
	0.05				
	$GARCHST$	0.0300	3.9074(0.05)	0.4342	4.6517(0.1)
	$GARCHCCST$	0.0325	2.9278 (0.1)	0.4225	3.8036
	$GARCHCCST_p$	0.0325	2.9278(0.1)	0.4221	3.8036
	0.025				
	$GARCHST$	0.0150	1.9110	0.1460	2.0942
	$GARCHCCST$	0.0150	1.9110	0.1460	2.0942
	$GARCHCCST_p$	0.0150	1.9110	0.1460	2.0942
LVMH	0.1				
	$GARCHST$	0.0825	1.4387	1.4353	1.4698
	$GARCHCCST$	0.0825	1.4387	1.4387	1.4698
	$GARCHCCST_p$	0.0825	1.4387	1.4386	1.4698
	0.05				
	$GARCHST$	0.0400	0.9014	0.7426	1.0893
	$GARCHCCST$	0.0400	0.9014	0.7272	1.0893
	$GARCHCCST_p$	0.0400	0.9014	0.7358	1.0893
	0.025				
	$GARCHST$	0.0300	0.3860	0.3787	1.2187
	$GARCHCCST$	0.0275	0.0994	0.3589	1.1863
	$GARCHCCST_p$	0.0275	0.0994	0.3661	1.1863
Posco	0.1				
	$GARCHST$	0.0750	3.0143(0.1)	1.1725	4.0153
	$GARCHCCST$	0.0875	0.7219	1.0953	1.2223
	$GARCHCCST_p$	0.0875	0.7219	1.1006	1.2223
	0.05				
	$GARCHST$	0.0400	0.9014	0.6391	2.2386
	$GARCHCCST$	0.0500	0	0.5843	2.1118
	$GARCHCCST_p$	0.0500	0	0.5867	2.1118
	0.025				
	$GARCHST$	0.0175	1.0296	0.4043	1.2796
	$GARCHCCST$	0.0200	0.4399	0.3406	0.7673
	$GARCHCCST_p$	0.0200	0.4399	0.3414	0.7673

Table L.0.2: Spillover Simulations and Parameter Estimates

models	κ	α	β	l_1	r_1	m_1	m_2	**-LOGL**	**BIC**
real value	0.1	0.8	0.1	$Lower = -3$ and $Upper = 3$					
$\lambda = 1$ and $m_2 = 1$				$mean(l_1)$	$mean(r_1)$				
				0.9046	0.9046				
				$std(l_1)$	$std(r_1)$				
				0.0259	0.0259				
				$median(l_1)$	$median(r_1)$				
				0.9096	0.9096				
GARCHCCN	0.0824***	0.8263***	0.0852***	0.9742***	0.9672***	-27.0139**	30.7408***	6.7844e+003	1.3628e+004
	(0.0176)	(0.0263)	(0.0110)	(0.0071)	(0.0059)	(11.7751)	(8.1025)		
GARCH	0.0838***	0.8282***	0.0815***					6.8325e+003	1.3691e+004
	(0.0188)	(0.0285)	(0.0118)						
$\lambda = 0.8$ and $m_2 = 1$				$mean(l_1)$	$mean(r_1)$				
				0.9047	0.9047				
				$std(l_1)$	$std(r_1)$				
				0.0213	0.0213				
				$median(l_1)$	$median(r_1)$				
				0.9119	0.9119				
GARCHCCN	0.0857***	0.8210***	0.0893***	0.9804***	0.9752***	-34.6042	40.1636***	6.8038e+003	1.3667e+004
	(0.0166)	(0.0246)	(0.0117)	(0.0092)	(0.0049)	(25.4855)	(10.9409)		
GARCH	0.0883***	0.8229***	0.0825***					6.8421e+003	1.3710e+004
	(0.0189)	(0.0276)	(0.0115)						
$\lambda = 0.8$ and $m_2 = 2$				$mean(l_1)$	$mean(r_1)$				
				0.9158	0.9158				
				$std(l_1)$	$std(r_1)$				
				0.0174	0.0174				
				$median(l_1)$	$median(r_1)$				
				0.9223	0.9223				
GARCHCCN	0.0902***	0.7932***	0.1158***	0.9777***	0.9752***	-44.9300***	41.7272***	6.8351e+003	1.3730e+004
	(0.0149)	(0.0265)	(0.0120)	(0.0051)	(0.0047)	(14.8384)	(11.0333)		
GARCH	0.0922***	0.7971***	0.1085***					6.9044e+003	1.3834e+004
	(0.0178)	(0.0268)	(0.0126)						
$\lambda = 1$ and $m_2 = 2$				$mean(l_1)$	$mean(r_1)$				
				0.9159	0.9159				
				$std(l_1)$	$std(r_1)$				
				0.0179	0.0179				
				$median(l_1)$	$median(r_1)$				
				0.9219	0.9219				
GARCHCCN	0.0694***	0.8341***	0.0997***	0.9772***	0.9745***	-49.1766***	34.5543***	6.9524e+003	1.3964e+004
	(0.0131)	(0.0207)	(0.0122)	(0.0040)	(0.0054)	(12.4184)	(10.5648)		
GARCH	0.0728***	0.8360***	0.0931***					7.0385e+003	1.4103e+004
	(0.0135)	(0.0205)	(0.0107)						

Notes: *$p < .05$, **$p < .01$, ***$p < .001$

Table L.0.3: Fitted GARCH models with Student-t tails

models	κ	α	β	v	l_1	r_1	m_1	m_2	**-LOGL**	**BIC**
ChinaTrust										
$GARCHST$	0.0257^{***}	0.9304^{***}	0.0696^{***}	4.8250^{***}					6.0758e+03	1.2184e+04
	(0.0122)	(0.0110)	(0.0114)	(0.4698)						
$GARCHCCST$	0.0354^{*}	0.9273^{***}	0.0693^{***}	4.4440^{***}	0.9254^{***}	0.9317^{***}	-5.6491^{***}	7.2380^{***}	5.8937e+003	1.1843e+004
	(0.0150)	(0.0127)	(0.0152)	(0.6304)	(0.0097)	(0.0078)	(1.0740)	(1.1598)		
$GARCHCCST_p$	0.0322^{*}	0.9271^{***}	0.0723^{***}	4.2646^{***}	0.9199^{***}	0.9343^{***}	5.2641^{***}	8.8194^{***}	5.8824e+03	1.1829e+04
	(0.0152)	(0.0119)	(0.0134)	(0.4960)	(0.0101)	(0.0068)	(1.0006)	(1.1339)		
Clevo										
$GARCHST$	0.0652^{***}	0.8913^{***}	0.1087^{***}	5.9269^{***}					8.8373e+03	1.7708e+04
	(0.0290)	(0.0144)	(0.0150)	(0.5954)						
$GARCHCCST$	0.0774	0.8787	0.1213	4.3080	0.8895	0.8896^{***}	-3.1660	4.0282	8.3340e+03	1.6734e+04
	(3.0709)	(0.9440)	(2.0368)	(108.9981)	(0.4886)	(0.1720)	(3.5063)	(6.3290)		
$GARCHCCST_p$	0.0781^{***}	0.8795^{***}	0.1205^{***}	4.3009^{***}	0.8904^{***}	0.8986^{***}	4.0024^{***}	5.7081^{***}	8.3288e+03	1.6723e+04
	(0.0299)	(0.0159)	(0.0176)	(0.3633)	(0.0062)	(0.0054)	(0.2852)	(0.3666)		
GDPower										
$GARCHST$	0.0963^{***}	0.9011^{***}	0.0989^{***}	3.3357^{***}					6.9979e+03	1.4028e+04
	(0.0394)	(0.0216)	(0.0211)	(0.2193)						
$GARCHCCST$	0.1450	0.8860	0.1140	3.1541^{***}	0.9999^{***}	0.9999^{***}	$-1.6081e+04^{***}$	$1.0490e+04^{***}$	6.6203e+03	1.3639e+04
	(1.3935)	(0.5898)	(0.1221)	(3.3092)	(1.6106e-05)	(2.0927e-05)	(1.6002e+03)	(1.0465e+03)		
$GARCHCCST_p$	0.2076^{***}	0.8423^{***}	0.1577^{***}	3.1552^{***}	0.9962^{***}	0.9986^{***}	151.0197^{***}	551.9741^{***}	6.8605e+03	1.3786e+04
	(0.0445)	(0.0175)	(0.0160)	(0.0874)	(0.0004)	(0.0002)	(16.6000)	(57.7680)		
Lotes										
$GARCHST$	0.0304^{***}	0.9183^{***}	0.0817^{***}	4.2748^{***}					3.5066e+003	7.0426e+003
	(0.0291)	(0.0273)	(0.0245)	(0.4430)						
$GARCHCCST$	0.0480	0.9072	0.0928	3.4540	0.9119^{***}	0.9288^{***}	-4.1141	8.6786	3.2643e+003	6.5866e+003
	(0.8923)	(0.8948)	(0.6751)	(42.3794)	(0.1941)	(0.1505)	(10.0638)	(10.9974)		
$GARCHCCST_p$	0.0478	0.9078^{***}	0.0922	3.4441	0.9067^{***}	0.9319^{***}	4.6274	10.8804^{***}	3.2639e+003	6.5867e+003
	(0.7374)	(0.3093)	(0.4886)	(15.4494)	(0.1050)	(0.0743)	(4.4027)	(1.5712)		
LVMH										
$GARCHST$	0.0345^{***}	0.9214^{***}	0.0708^{***}	7.6150^{***}					7.2391e+03	1.4511e+04
	(0.0106)	(0.0100)	(0.0107)	(0.8951)						
$GARCHCCST$	0.0364^{***}	0.9224^{***}	0.0684^{***}	7.7099^{***}	0.9999^{***}	1.0000^{***}	$-1.5574e+04^{***}$	$2.6690e+04^{***}$	7.0975e+03	1.4261e+04
	(0.0098)	(0.0090)	(0.0076)	(0.8636)	(9.1353e-06)	(5.6598e-06)	(1.8086e+03)	(3.0983e+03)		
$GARCHCCST_p$	0.0370^{***}	0.9218^{***}	0.0679^{***}	7.8841^{***}	1.0000^{***}	0.9864^{***}	$2.4608e+04^{***}$	43.4788^{***}	7.1557e+03	1.4377e+04
	(0.0101)	(0.0095)	(0.0078)	(0.8864)	(6.9797e-06)	(6.7417e-04)	(3.0879e+03)	(3.3642)		
Fubon										
$GARCHST$	0.0538^{***}	0.9206^{***}	0.0702^{***}	4.7636^{***}					6.1309e+03	1.2294e+04
	(0.0235)	(0.0181)	(0.0154)	(0.4538)						
$GARCHCCST$	0.0604^{***}	0.9202^{***}	0.0628^{***}	4.9131^{***}	0.8761^{***}	0.9396^{***}	-2.5817^{***}	8.3922^{***}	6.0083e+03	1.2081e+04
	(0.0241)	(0.0189)	(0.0158)	(0.5739)	(0.0156)	(0.0083)	(0.5566)	(1.5007)		
$GARCHCCST_p$	0.0601^{**}	0.9197^{***}	0.0649^{***}	4.7740^{***}	0.9020^{***}	0.9420^{***}	4.5926^{***}	10.1136^{***}	6.0098e+03	1.2084e+04
	(0.0248)	(0.0188)	(0.0160)	(0.6032)	(0.0118)	(0.0074)	(0.8579)	(1.6642)		
Posco										
$GARCHST$	0.0379^{***}	0.9259^{***}	0.0705^{***}	5.6424^{***}					7.5632e+03	1.5159e+04
	(0.0139)	(0.0101)	(0.0101)	(0.5481)						
$GARCHCCST$	0.0385^{***}	0.9259^{***}	0.0700^{***}	5.6702^{***}	0.9847^{***}	0.9048^{***}	-15.8378^{***}	1.6549^{***}	7.5529e+03	1.5171e+004
	(0.0146)	(0.0102)	(0.0103)	(0.5392)	(0.0125)	(0.0283)	(17.4381)	(0.8544)		
$GARCHCCST_p$	0.0381^{***}	0.9254^{***}	0.0715^{***}	5.5401^{***}	1.0000^{***}	0.9390^{***}	-4.0887^{***}	4.1689^{***}	7.5560e+03	1.5177e+04
	(0.0134)	(0.0097)	(0.0107)	(0.5281)	(0.0028)	(0.0208)	(0.3102)	(2.0492)		

Notes: $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$

Table L.0.4: Simulated Moments with a data size of 50,000

Data/Fitted Models	**mean**	**variance**	**skewness**	**kurtosis**	$E(u_t u_{t-1})$	$E(u_t^2 u_{t-1}^2)$	S
ChinaTrust	0.0228	4.7042	-0.0222	5.1582	0.1197	49.4065	
$GARCHST$	-0.0193	10.1892	-0.0589	74.0920	-0.1054	1.3241e+003	1.6296e+006
$GARCHCCST$	0.0261	5.4334	-0.0328	4.5925	-0.0349	44.5487	**24.4734**
$GARCHCCST_p$	0.0291	4.4976	0.0607	5.0888	-0.0054	31.7961	310.1954
Clevo	0.0493	8.0712	0.0562	3.5926	0.6657	110.1570	
$GARCHST$	-0.0231	25.8024	-1.2193	133.2548	-0.7911	1.6190e+004	2.5857e+008
$GARCHCCST$	0.0555	7.6436	0.0184	3.7620	0.0032	87.7507	**502.6961**
$GARCHCCST_p$	0.0713	7.0288	0.0321	4.0161	0.0378	77.3208	1.0799e+003
Fubon	0.0136	3.9925	-0.0871	5.3566	-0.0289	29.4134	
$GARCHST$	-0.0014	6.5113	0.1471	39.9018	-0.0094	303.4114	7.6275e+004
$GARCHCCST$	-0.0043	4.4142	-0.0476	5.1025	0.0011	31.6812	**5.3881**
$GARCHCCST_p$	-0.0067	3.9771	-0.0296	5.3234	0.0439	24.3476	25.6727
GDPower	0.0503	5.1081	0.0213	6.9328	0.0908	61.6979	
$GARCHST$	-0.0194	12.2799	-0.6503	49.3130	-0.1226	1.6032e+003	2.3781e+006
$GARCHCCST$	-0.0033	3.8053	-0.0903	6.5862	-0.0024	22.9209	1.5055e+003
$GARCHCCST_p$	-0.0080	4.7540	-0.0716	7.5048	-0.0838	45.0616	**277.2595**
Lotes	0.0449	6.7640	0.2875	4.2639	1.1065	86.0828	
$GARCHST$	-0.0008	12.9794	0.2553	96.7197	-0.2383	3.8137e+003	1.3904e+007
$GARCHCCST$	0.1741	6.5900	0.2109	4.3590	0.0341	68.2735	**318.3817**
$GARCHCCST_p$	0.1385	5.4865	0.2935	4.9974	0.1135	50.5816	1.2635e+003
LVMH	0.0137	4.0454	0.1035	6.5333	0.0458	31.3893	
$GARCHST$	0.0022	4.2086	0.0264	13.2048	-0.0583	64.7740	1.1591e+003
$GARCHCCST$	0.0019	3.3803	-0.0328	5.2883	-0.0183	18.4040	170.6332
$GARCHCCST_p$	0.0199	3.7367	0.1829	6.1638	-0.0053	25.5796	**33.9934**
Posco	0.0237	5.4131	0.0012	7.6805	0.2872	65.3117	
$GARCHST$	0.0158	16.8355	1.1817	267.6687	0.0638	1.7615+004	3.0806e+008
$GARCHCCST$	0.0069	4.4798	0.0364	5.7016	-0.0246	34.6737	**943.5703**
$GARCHCCST_p$	0.0141	4.4465	0.0815	5.6789	0.0113	32.9886	1.0498e+003

Appendix M

mfiles

Table M.0.1: mfiles

mfile name	Description
	TN
NtE	Finding the parameters
randraw	Simulation
tnpdf	the pdf function
tncdf	the cdf function
	CN
cnfit	Finding the parameters
cnrnd	Simulation
cnpdf	the pdf function
cncdf	the cdf function
	CCN
ccnfit	Finding the parameters
ccnllf	-LOGL of CCN
ccnrnd	Simulation
ccn1st	$E(x)$ and x follows CCN
ccn2nd	$E(x^2)$ and x follows CCN
ccn3rd	$E(x^3)$ and x follows CCN
ccn4th	$E(x^4)$ and x follows CCN
ccnmean	mean of x and x follows CCN
ccnvar	variance of x and x follows CCN
ccnskewness	skewness of x and x follows CCN
ccnkurtosis	kurtosis of x and x follows CCN
pm	the ccncdf between a_1 and b_1
ccncdf	the cdf function for ccn
ccnpdf	the pdf function for ccn
	generalized GED
ggedfit	Finding the parameters
gedrnd	Simulation of standardized GED
	truncated generalized GED
tgedfit	Finding the parameters
tgedllf	the -LOGL
tgedrnd	Simulation of truncated standardized GED
gtgedrnd	Simulation of truncated generalized GED
	censored generalized GED
cgedfit	Finding the parameters
cgedllf	the -LOGL
cgedrnd	Simulation of censored standardized GED
gcgedrnd	Simulation of censored generalized GED

Continued on next page

Table M.0.1 – continued from previous page

mfile name	Description
	CC generalized GED
ccged	Finding the parameters
ccgedpdf	the pdf of ccged
ccgedcdf	the cdf of ccged
ccgedllf	the -LOGL
ccgedrnd1	Simulation of CC generalized GED
ccgedskewness	the skewness of ccged
ccgedkurtosis	the kurtosis of ccged
ccgedvar	the variance of ccged
ccgedmean	the mean of ccged
ccgedfirst	the mean of ccged
ccgedsecond	the second moment of ccged
ccgedthird	the third moment of ccged
ccgedfourth	the third moment of ccged
firststdtged	un-centred first moment of std ged with two bounds
secondstdtged	un-centred second moment of std ged with two bounds
thirdstdtged	un-centred third moment of std ged with two bounds
forthstdtged	un-centred fourth moment of std ged with two bounds
	generalized Student-t
st	Finding the parameters
stllf	the -LOGL
stdtrnd	Simulation of standardized Student-t
	truncated generalized Student-t
truncatedst	Finding the parameters
tstrnd	Simulation of truncated standardized Student-t
gtstrnd	Simulation of truncated generalized Student-t
	censored generalized Student-t
censoredst	Finding the parameters
cstrnd	Simulation of truncated standardized Student-t
gcstrnd	Simulation of truncated generalized Student-t
	CC generalized Student-t
scnstfit	Finding the parameters
scnstllf	the -LOGL of CC generalized Student-t
scnstrnd	Simulation of CC generalized Student-t
scnstpdf	the pdf of CC generalized Student-t
ccstcdf	the cdf of CC generalized Student-t
ccstvar	variance of ccst
ccstsecond	un-centred second moment of ccst
ccstmean	mean of ccst
ccstfirst	un-centred first moment of ccst
ccstthird	un-centred third moment of ccst
ccstfourth	un-centred fourth moment of ccst
ccstskewness	skewness of ccst
ccstkurtosis	kurtosis of ccst
firststdtst	un-centred first moment of stdtst with two bounds
secondstdtst	un-centred second moment of stdtst with two bounds
thirdstdtst	un-centred third moment of stdtst with two bounds
forthstdtst	un-centred fourth moment of stdtst with two bounds
gt1	un-centred first moment of generalized Student-t with two bounds
gt2	un-centred 2nd moment of generalized Student-t with two bounds
gt3	un-centred 3rd moment of generalized Student-t with two bounds
gt4	un-centred 4th moment of generalized Student-t with two bounds
	time varying functions
	GARCH
insamplevarn	the in-sample VaRs
outsamplevarn	find the out-sample VaRs
	GARCH with TN
ugarchv1	Finding the parameters
ugarchsim1	Simulation
insamplevartn	find the in-sample VaRs
outsamplevartn	find the out-sample VaRs
	GARCH with CN
ugarchvcn	Finding the parameters
ugarchsimcn	Simulation

Continued on next page

Table M.0.1 – continued from previous page

mfile name	Description
insamplevarcn	find the in-sample VaRs
outsamplevarcn	find the out-sample VaRs
	GARCH with CCN
ugarch600jenota	Finding the parameters
ugarchllf600jnota	the -LOGL
ugarchsim600jnota	Simulation
sim600j	Monte Carlo simulation of GARCHCCN
insamplevar	find the in-sample VaRs
outsamplevar	find the out-sample VaRs
	GARCH with fat tails: GED or Student-t
fattailed_garch	Finding the parameters
garchged	finding the parameters for garch with ged tailes
garchgedllf	the -LOGL for finding the parameters for garch with ged tailes
garchst	finding the parameters for garch with st tailes
garchstllf	the -LOGL for finding the parameters for garch with st tailes
fattailed_garchlikelihood	the -LOGL
ugarchsimged	Simulation with GED tails
ugarchsimst	Simulation with Student-t tails
insamplevarged	find the value at risk given the fitted GARCH model with GED
insamplevarst	find the value at risk given the fitted GARCH model with ST
outsamplevarged	find the value at risk given the fitted GARCH model with GED
outsamplevarst	find the value at risk given the fitted GARCH model with ST
	GARCH with truncated GED
ugarchtged	Finding the parameters
ugarchllftged	the -LOGL
ugarchsimtged	Simulation
	GARCH with censored GED
ugarchcged	Finding the parameters
ugarchllfcged	the -LOGL
ugarchsimcged	Simulation
	GARCH with CC GED
garchccgednew	Finding the parameters
ugarchllfccged10	the -LOGL
ugarchsimccged10	Simulation
	GARCH with truncated Student-t
ugarchtst	Finding the parameters
ugarchllftst	the -LOGL
ugarchsimtst	Simulation
	GARCH with censored Student-t
ugarchcst	Finding the parameters
ugarchllfcst	the -LOGL
ugarchsimcst	Simulation
	GARCH with CC Student-t
garchccstnew	Finding the parameters
ugarchllfccst10	the -LOGL
ugarchsimccst10	Simulation
	$GARCHCCST_p$
ugarchccstkk	Finding the parameters
ugarchllfccstkk	the -LOGL
cdfinvccstkk	given the value of cdf, find the variable
ccstkkrnd	generate random variables
insamplevarccstkk	find the in-sample VaRs
outsamplevarccstkk	find the out-sample VaRs
ugarchsimccstkk	simulation of data following garch with $ccst_p$
ccstcdfkk	the cdf of a variable under $CCST_p$ distribution
ccgedcdfkk	the cdf of a variable under $CCGED_p$ distribution
	group mapping
spill200	find the spillover value using function
spillemp	find the spillover value using mapping rule
mapping10	mapping a normal variable to a ccn rnd variable
spill8	using the reversed mapping rule to calculate $spill_i$ for $i = 1, 2$
	one to one mapping

Continued on next page

Table M.0.1 – continued from previous page

mfile name	Description
mappingback	if a ccn variable is given, find its true value
mappingforward	if a normal variable is given, find its matching ccn variable
ugarchllfmapping	the $-LOGL$ of a GARCHCCN model with both 1st and 2nd moment spillover
ugarchmapping	find the parameters of a GARCHCCN model with both 1st and 2nd moment spillover
	find value at risk
cdfinvtn	find the value at risk for TN given p-value of x
cdfinvcn	find the value at risk for CN given p-value of x
cdfinvccn	find the value at risk for CCN given p-value of x
cdfinvccst	find the value at risk for CCST given p-value of x
cdfinvccged	find the value at risk for CCGED given p-value of x
	simulation with spillover
spillmap	simulations of a time series with spillover according to section 3.5.1
	Laplace pdf
laplacepdf	the pdf of Laplace distribution
laplacecdf	the cdf of Laplace distribution
laplacellf	the negative log likelihood of the Laplace distribution
laplacefit	find the fitted parameters of the Laplace distribution
	clustered censored Laplace pdf
cclaplacefit	find the fitted parameters of the clustered censored Laplace distribution
ccnllflaplace	the negative log likelihood of the clustered censored Laplace distribution
cclaplacepdf	the pdf of the cclaplace
cclaplacecdf	the cdf of the cclaplace

Appendix N

Mappings

Figure N.1: the mapping between x and y: symmetric mapping

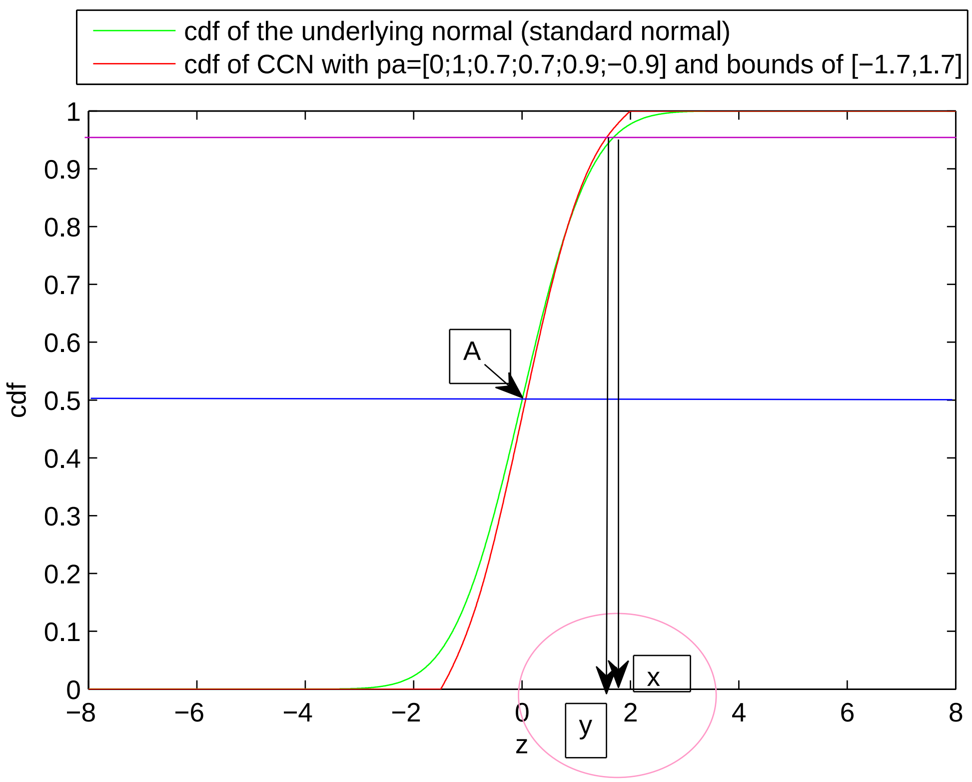


Figure N.2: the mapping between x and y: asymmetric mapping

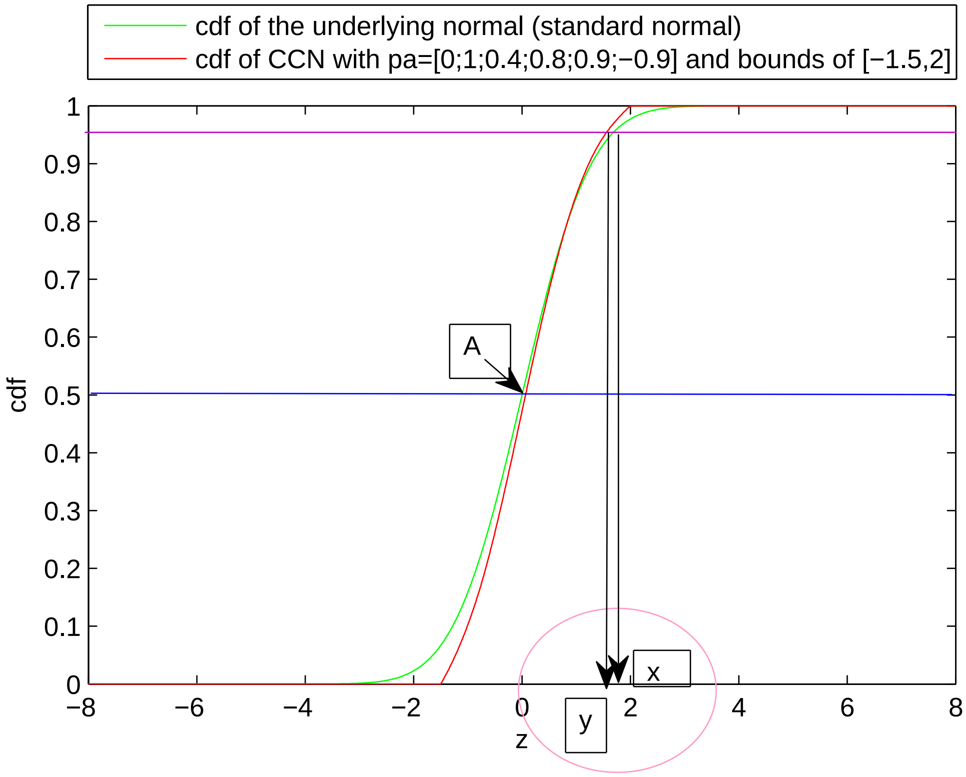


Figure N.3: the mapping between x and y: TN

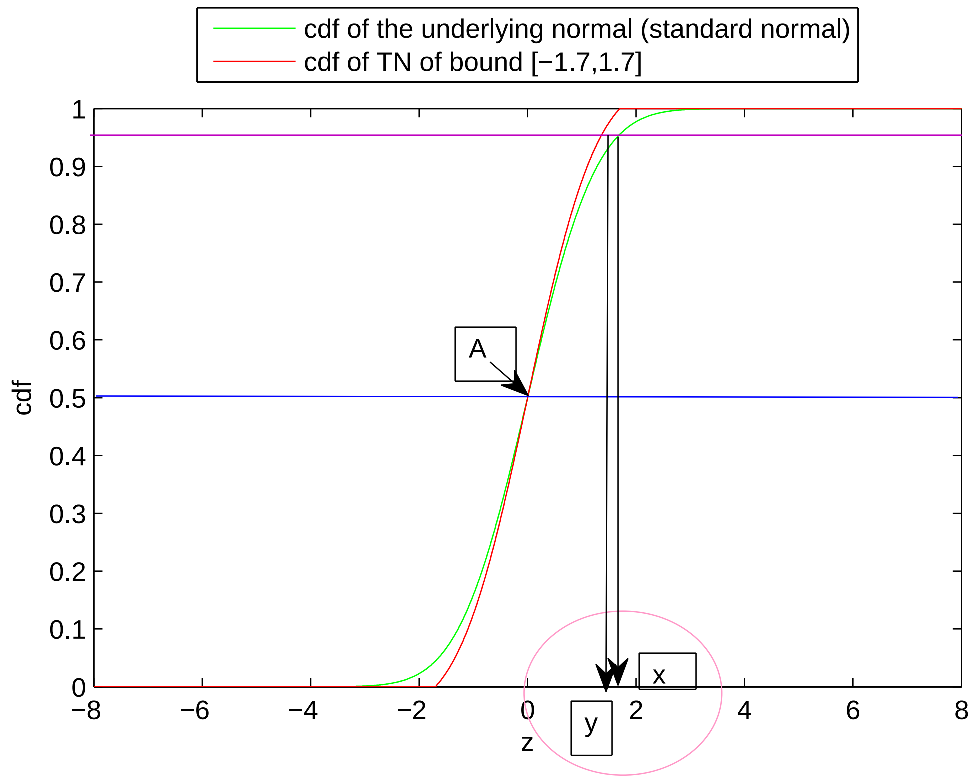


Figure N.4: Latent and Observed Values with Bounds of $[-5, 5]$

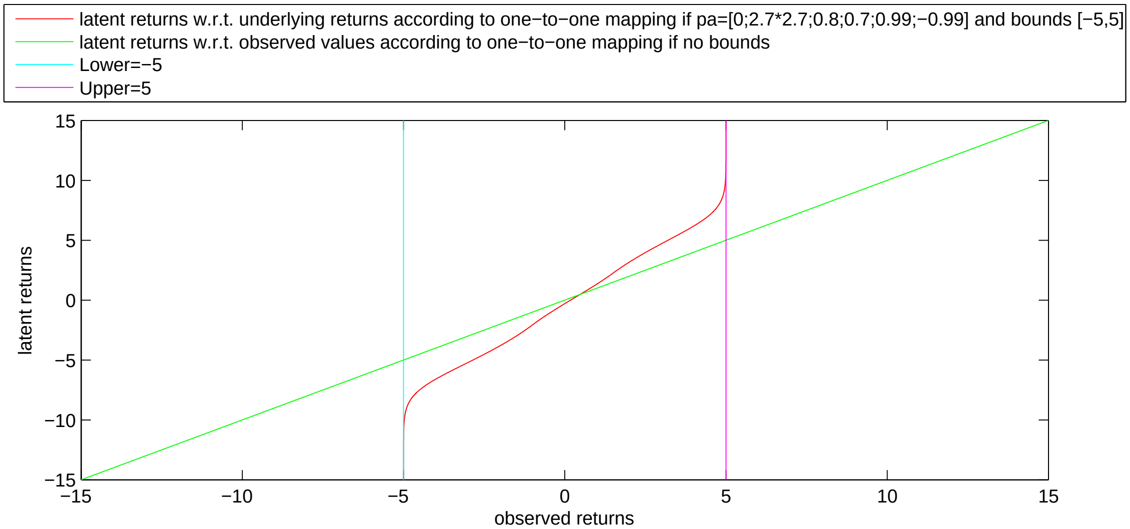


Figure N.5: Latent and Observed Values with Bounds of $[-7.5, 7]$

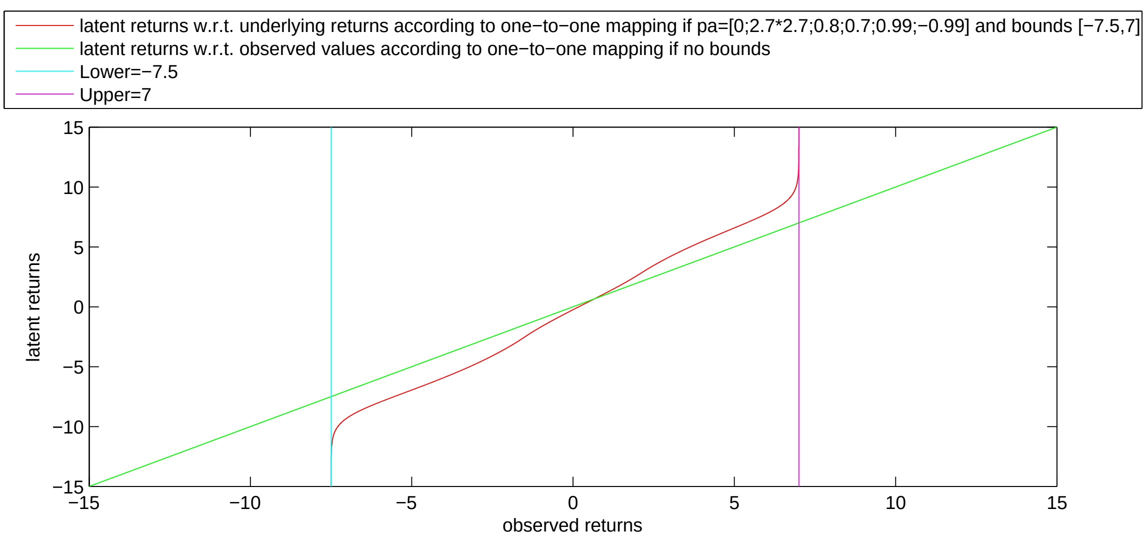


Figure N.6: CDF v.s. x with Bounds of $[-5, 5]$ and $pa = [0; 2.7 * 2.7; 0.8; 0.7; 0.99; -0.99]$

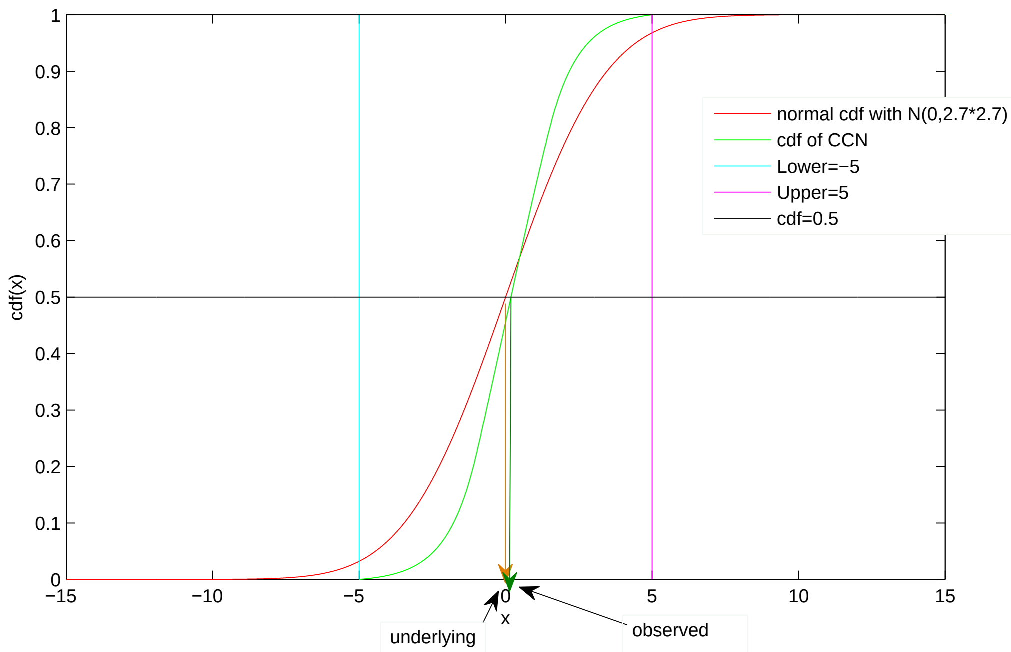


Figure N.7: CDF v.s. x with Bounds of $[-7.5, 7]$ and $pa = [0; 2.7 * 2.7; 0.8; 0.7; 0.99; -0.99]$

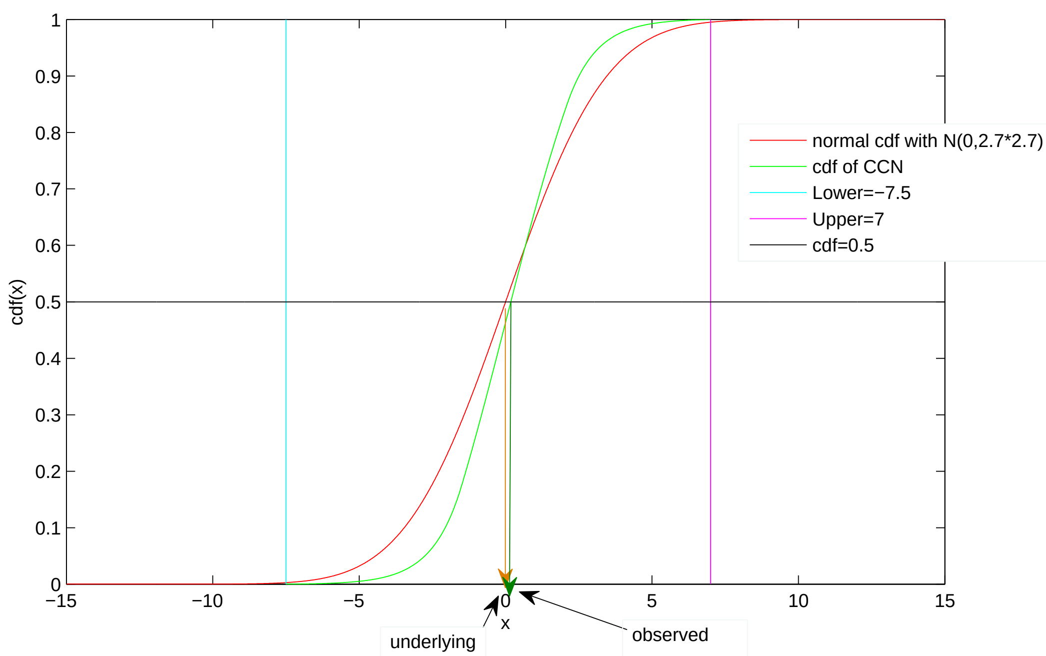
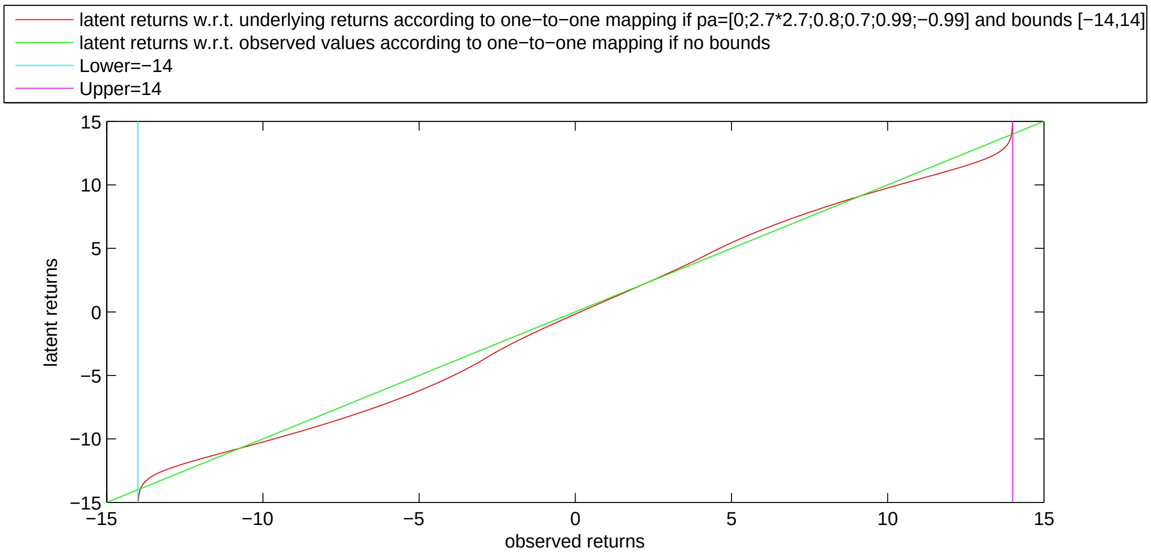


Figure N.8: Latent and Observed Values with Bounds of $[-14, 14]$



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