Arbitrage profit from pairwise correlation: Evidence from Thailand

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กลยุทธ์การทำกำไรจากผลต่างราคาหุ้นที่มีความสัมพันธ์กันในตลาดหลักทรัพย์แห่งประเทศไทย

น.ส.สลิลพร เดชะศิริประภา

สารนิพนธ์นี้เป็นส่วนหนึ่งของการศึกษาตามหลักสูตรปริญญาวิทยาศาสตรมหาบัณฑิต
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By	Miss Salinporn Dachasiriprapha
Field of Study	Finance
Thesis Advisor	Narapong Srivisal, Ph.D.

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สลิลพร เดชะศิริประภา : กลยุทธ์การทำกำไรจากผลต่างราคาหุ้นที่มีความสัมพันธ์กันในตลาดหลักทรัพย์แห่งประเทศไทย. (Arbitrage profit from pairwise correlation: Evidence from Thailand) อ.ที่ปรึกษาหลัก : อ. ดร.นราพงศ์ ศรีวิศาล

This paper aims to examine the usefulness of the Dynamic Conditional Correlation in the aspect of pair trade. Since one of the challenges in the pair trading is pair formation, this research would like to fulfill and find a new method for pair formation. Also, not only find the effective way to form pair we also examine whether this strategy can generate an abnormal return by constructs the portfolio where short one stock and long another one, by this investor can enjoy a 2-way price spread. The finding in this suggests that first by using Dynamic Conditional Correlation to form pair can generate higher of winning pair than losing pair. The secondary, abnormal return does exist in Stock Exchange of Thailand in a specific period. Also, using price information from extraordinary events can generate an annualized abnormal return around 39% higher than the normal period.

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Salinporn Dachasiriprapha : Arbitrage profit from pairwise correlation: Evidence from Thailand. Advisor: Narapong Srivisal, Ph.D.

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Field of Study:	Finance	Student's Signature
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Academic Year:	2020	Advisor's Signature
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1.INTRODUCTION

A. Background and significance of the problem

In the world of the financial market, there are groups of investors who have different trading strategies seeking for an opportunity to maximize their profit in the Equity market where stock trading activities occurred. A lot of trading strategies rely on technical tools and historical data which challenge EMH. According to the Efficient Market Hypothesis which consists of three levels: Weak Form, Semi – Strong Form, and Strong Form.

- Weak Form: Stock price already absorbs all information in market trading data which technical analysis on average cannot generate an abnormal return.
- Semi – Strong Form: Stock price already reflects all the public information which even fundamental analysis will not outperform the market.
- Strong Form: Stock price already reflects all public and private data which even use internal information will not create an abnormal return.

Therefore, profit from historical data and technical tools will point to market inefficient. Nowadays, High-frequency trading (HFT) becomes one of the topics that investors are interested in. HFT is characterized by the length of the holding period trying to capture the profit within a short period of time (Cartea & Penalva, 2012). Many strategies have been widely used in HFT and one of them is pair trade. Pair trade, which was introduced by Gerry Bamberger and Nunzio Tartaglia in 1980, is the well-known trading strategy that enables traders to make a profit in any market condition: uptrend, sideways, and downtrend. This strategy depends on the historical data of correlated securities, once the deviation occurs short and long strategy will take place. To simplify, two stocks that their price usually moves together when the unusual gap between the two stocks occur, traders will buy the stock that its price relatively low compare to another stock and sell the stock that its price relatively high. Pair trade or market neutral trading strategy is the strategy that matches between short and long positions for correlated pairs. The profit of the trading pair is derived from the difference of the price change from two securities. Therefore, pair trade is not considered as a risk-free strategy since the profit relies on the selection of pairs and efficient trading rule to identify the gap. As mentioned, the challenge of statistical arbitrage using pair trade strategy is the selected pair stock and the right position for each stock. The rest of this paper arranged as follows. Section 2: discusses the existing literature review and research contributions. Section 3: Data preparations and Methodology that have been used in this paper.

B. Objective

The main objective of this paper is to find the new way to form pairs to trade in the pair trading which also aims to study and examine the profitability of daily trade investment using pair trade strategy based on dynamic conditional correlation.

Moreover, this study would like to capture extraordinary events which are Thailand flooded in 2011 and political issues in 2013 to find the answer to whether the crisis period can generate a higher return by using pair trade strategy compare to the normal period.

C. Research Hypothesis

Many previous researches studied about pair trade while using the co-integration and correlation framework and found a positive abnormal return. According to Gatev. et el. (2006), the strength of pair trading is investor make a decision without feeling and their own ability since there will be replaced by the clear rule and method. Main concept of pair trading is to invest in two assets that price closely related to one another. When abnormally divergence occur, long shot position will be taken. As mentioned, key success is pair selection, since high frequent trade become more popular among investors but cointegration greatly benefit in long run relationship, therefor, by employed DCC where daily correlation change over times and short run deviation can be captured should add the benefit to pair trading world. By that this paper would like to examine;

H_1: Pair trade based on dynamic conditional correlation can generate number winning pairs higher than losing pairs.

According to Do and Faff (2010) find that pair-trading strategies performed very well during the 1970s and 1980s, including during the 1987 crash. After the mentioned period, there is a decline trend of pair-trading profitability in the U.S. stock market but still exist. To support the finding in hypothesis 1 and to find whether abnormal return still exist, this paper will also examine:

H_2: Pair stock from dynamic correlation can generate a positive abnormal return

As mentioned earlier, pair trade performed well in a specific period such as 1987 crash and Isogai (2015) focused on pairwise correlation of Japanese stock returns to study the correlation dynamically and found that during the crisis period stocks seem to have higher correlation than usual. As correlation will be more intense during those periods, therefor, by using price information from extra ordinary events should generate higher number of pairs. The reason is that in normal period, two assets may not highly correlated to one another but stocks seem to reflect bad situation in the same direction, therefor, the correlation between assets at that time should be higher result in higher mean correlation than usual. The more intense, the greater number of pair generated with higher chance to trade. So, this paper would like to find the answer whether using price from events period to form pair can generate higher abnormal return.

H_3: By using stock price from period where extra ordinary events occurred to form pair can generate a higher abnormal return than normal period.

D. Conceptual and framework

Statistical Arbitrage is a trading strategy that uses data mining to compute and find the mispricing asset. Pair trade is one of the methods used in statistical arbitrage. The concept of the pair trade is matching two stocks that are highly correlated with a short and long position. This paper aims to focus on short term investment between pairwise stock correlation, therefore, to capture the real-time correlation, a dynamic correlation approach is a key method to use in this paper.

Dynamic Conditional Correlation

The reason we employed the DCC-GARCH model which was proposed by Engel (2002) because the model implements the dynamic of correlation matrix changes without moving window period. Static correlation with the moving window period can have an impact from the past large shock longer and it can distort the current correlation. This problem can be solved by using a shorter period of time but it might harm correlation stability and also have some limitation of the number of observations. Since DCC-GARCH consists of three parts which are mean part, volatility part, and DCC part so this model can calculate the dynamic correlation without moving window period. The volatility of the fluctuation will be reduced out of the return matrix so the matrix will show the correlation of the point in time from the pairwise correlation. By using dynamic conditional correlation where correlation change day by day will allow us to benefit to find the deviated pair to trade. There are many literatures studied about pair trading which as mentioned before one of the challenges in this strategy is how to form pair which DCC is not only use to form pair but will be use to forecast correlation to find the day that correlation deviate from its mean.

Trading Concept

To determine the deviation, this study use standard deviation to capture the abnormally divergence with the expect that the price of the two stock will converge to move as usual in the future. Standard deviation is one of the most common use to detect the abnormal pricing that has been employed in many previous researches. We use below 2 standard deviation of its mean because as normal curve there will be only 2.5% that will fall below its mean. The reason we focus only below its mean correlation because the lower the correlation reflect the direction among assets in the difference way. As the value of the correlation is between -1 and 1 where 1 indicate the perfectly move in the same direction. So, the closer to 1 the higher chance to move in the same direction between 2 assets which is not match with pair trade where one stock expected go up and another one expected to go down. The closer to -1 indicate the difference direction among the two assets. In pair trade world, an abnormally breakdown or movement need to be captured first which 2 Standard deviation are the common criteria in pair trading will be used to detect the abnormal movement between the two stocks. Figure 1 was one of the example pairs in this study, over a year correlation among assets vary day by day but there were only 4-5 days that the correlation below 2 standard deviation from its mean.

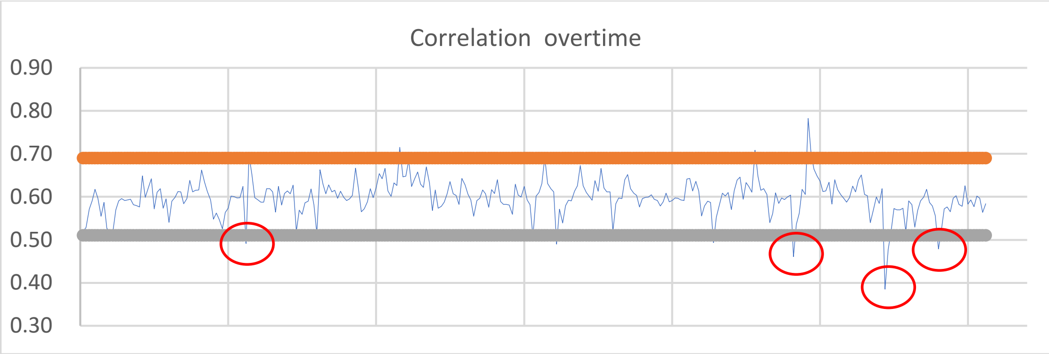

Figure 1-Correlation overtime

As it's not happened quiet often, it can be considered as an abnormal one. Also, once the breakdown happened, they normally converge back to trade around its mean. This study uses only pairs with the positive correlation as positive correlation refer to the same direction whether up-up or down-down once the correlation falls below its mean there should be one stock to go up and one to go down which match with the pair trade to long stock that will go up and short one that will go down. The reason we not take action on the day that the correlation deviated more than 2SD because the higher the correlation the closer to one which means that both assets will move in the same direction. If both long and short were taken on that day profit and loss will be offset each other. As mentioned, positive correlation and below 2 standard deviation will be use in this study as it matches with pair trade strategy. To initiate trading action for given pair, we use 2 standard deviation below its mean as a threshold for correlation breakdown. However, if a pair was selected to trade in the previous trading day, we use 0.5 SD below mean correlation as a threshold instead because the pair should still be on convergence toward normal correlation around its mean. If the correlation becomes closer than 0.5 SD to the mean, no action will be taken on that day as it signals being converged. It is important to note that we do not use 0.5 SD below mean as initial cut off because as normal curve there is high chance that the correlation can falls in a range of 0.5 SD below its mean which not considered as abnormal divergence. In addition, in order to select a pair to trade, the mentioned thresholds are considered together with the criteria for identifying long and short stock as follow:

- Short stock that previous daily return higher than their average daily return from the formation period.
- Long stock that previous daily return lower than their average daily return from the formation period.

All the given pairs that has been selected to trade will be follow the same trading steps as figure 1 trading concept. As we stated above about extra ordinary event period, since this paper study during the period that cover 2 extra ordinary events which are Thailand mega flood in 2011 and political protest 2013 – 2014. As these 2 events were not often occur and both effect business operation such as business temporary close and also decrease in forecasted GDP during that events. Since stock seems to reflect the bad situation in the same direction, by using the information from that period to form pair the result will be difference from normal period. There will be some specific periods that will be affected from these issues which will be discussed more in the data preparation and empirical result later.

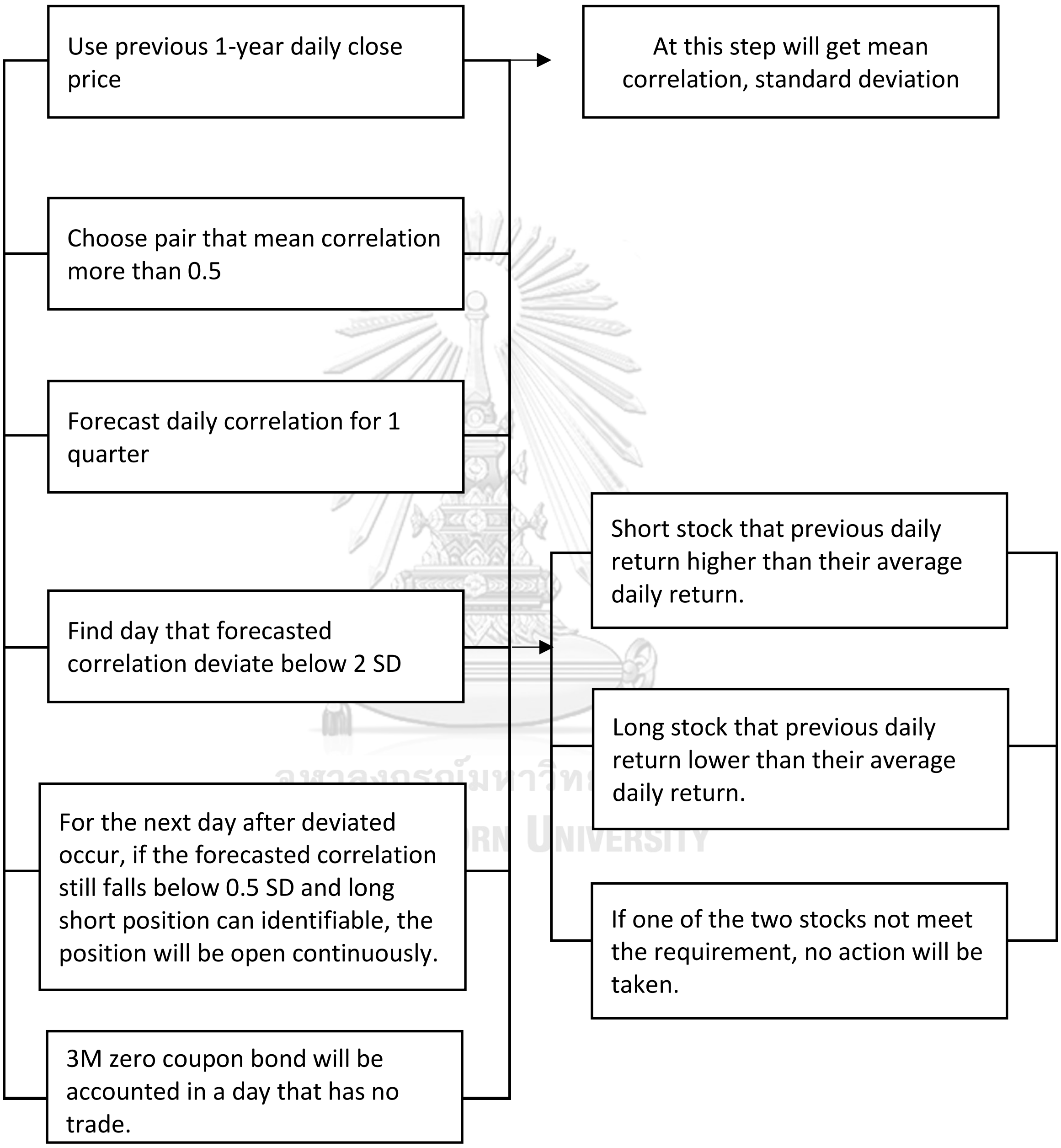

Figure 2- trading concept

2.LITERATURE REVIEW

A previous study was developed by Mantegna (1999) who studied the correlation of US stock network return by using Pearson's linear correlation and then built a minimum spanning tree in order to find the hierarchical structure of the network. There are many studies that have focused on the dynamic aspects of the correlation network using a moving window period to assess how the network changes such as Onnela et al. (2003a), Bonanno et al. (2004) and Kenett et al. (2010) with different focused. Onnela et al. (2003a), which studied a time-dependent for stock return of NYSE, concluded that the correlation network is robust by time and more intense during the crisis period. While Bonanno et al. (2004), study with different portfolios. Kenett et al. (2010) analyzed stationary correlations between stocks through the study of correlations. These previous research works have used Pearson's linear correlation of the sample returns, which is also used to calculate the dynamic correlation by shifting the observation period. There is much research using dynamic correlation method to study such as Thomas C. Chiang , Lin Tan & Huimin *Li (2007)* study the dynamic correlation of Chinese A-share and B-share market. They found that correlation coefficient between stock returns is time – varying and there is a substantial spillover effect from Asian crisis to Chinese-stock return correlation. Not only use dynamic correlation to study the relationship between stock but this method has been adopted to study the relationship between exchange rate and stock market return by *Hua Zhao (2010).* The result shows that there is no long-term equilibrium relationship between RMB real effective exchange rate and stock price. After that, *Isogai, 2016* found that by moving window period can have a distorted problem. Not only conclude about the problem but they also conclude that dynamic correlation by using DCC-GARCH which was developed by *Engel (2002)* can describe the change in correlation since it will reflect the change better and faster. They use an advanced type of volatility model with a dynamically change in correlation (DCC–GARCH) to control the volatility fluctuations. The conditional correlation matrices are estimated by using the DCC–GARCH model, which enables them to create a dynamic correlation network, also can capture the significant change in the asset return correlation. While *Walid Mensi, Shawkat Hammoudeh, Ahmet Sensoy ,and Seong-Min Yoon (2017)* use dynamic correlation to analyze the dynamic linkage and hedging strategies between Islamic and conventional sector equity indexes with the result provide optimal portfolio and asset allocation. For statistical arbitrage focusing on pair trade strategy, pair trade is a strategy that emerged from the quantitative group in the 1980s. There are many studies about this strategy such as *Vidyamurthy (2004)* proposed the cointegration framework, *Elliott et al. (2005)* mean-reverting properties. *Avellaneda and Lee (2010), Do and Faff (2010), Rad et al. (2016), and Liu et al. (2017)* also studied about pair trade. In the academic literature, *Gatev et al. (2006)* examined pair-trading strategies by using daily return over the of 1962–2002 which they use a distance filter between normalized historical price series to find profitable pairs, as a result the average annualized excess returns around 11% for self-financing portfolios. *Krauss (2017)* studied around 90 papers from 1987to 2015, and finds that *Gatev et al. (2006)* is the popular cited most pair trade use. *Krauss (2017)* concluded that the distance approach is the most concentrated one. In particular, *Gatev et al. (2006) and Do and Faff (2010)* are the two representative studies using the distance approach strategy which they find the profitable pair by using distance and frequency method separately. Using the same strategy and rules of *Gatev et al. (2006)* with the difference period, *Papadakis and Wysocki (2007)* find the average annualized excess returns up to 7.67% from pair trading. *Do and Faff (2010)* find that pair-trading strategies performed very well during the 1970s and 1980s, including during the 1987 crash. After the mentioned period, there is a decline trend of pair-trading profitability in the U.S. stock market. Nonetheless, in major bear markets such as during the crisis periods of 2001–2002 and 2007–2009 found significant profit from pair trade. *Jacobs and Weber (2015)* state that the persistence of pair-trading profitability may be affected by the dynamics and interaction of news, investor attention, and limits to arbitrage in the U.S. market. Some additional considerations can affect pair-trading profitability such as alternative frequency-distance filters, different lengths of trading period, and industry boundary. *Do and Faff (2010)* supplement the distance filter developed by *Gatev et al. (2006)* with a frequency one, also taking into consideration the industry boundary. On the other hand, *Do and Faff (2010)* show that portfolios of pair trades from the financial and utility sectors perform better than those from the industrial and transportation sectors. They also note that the frequency filter, or the number of zero-crossings, can help the distance filter find more profitable pairs. The combination of the Markov regime-switching and Vasicek models has been used by *Yang, Tsai, Shyu, and Chang (2016*) to execute the strategy on the S&P 500 stock from 2006 Jan–2012 Sep, they found that the shorter the trading period the better performance. They also showed that the trading rule outperforms mean-reverting stochastic methods and produces strong returns during the global financial crisis of 2008–2009. Not only in US stock market where pair trade has been studied, *Perlin (2009)* studied in Brazil market by using different frequencies of price data to test pair-trading profitability and the result show that by using daily frequency can outperform weekly and monthly data.

Research Contribution

This paper uses a statistical basis to study pair trade strategy. As mentioned early, one of the key successes in this strategy is to form a good pair. To select a good pair, we apply the dynamic correlation to find the correlated pair. The idea of this method is that the correlation intensity can change over time so it can capture the change in correlation between stocks. By this method, we can build the pairwise correlation stock more accurately. To our knowledge, there is no research using this approach in Stock Exchange of Thailand (SET) before. Moreover, this paper aim to benefit investors in Stock Exchange of Thailand who interested in daily trade and can implement this strategy to algorithm trade in the future.

3.DATA PREPARATION

Data preparation

As of December 2019, there were over 600 listed stock in Stock Exchange of Thailand. For this experiment, only stocks that were members of the SET100 between 2010 –2019 will be used to study. By definition, SET100 comprises 100 largest and most liquid stocks in the market and therefor are most likely to be investment-grade and least likely to be maliciously manipulated.

List of data

Data	Description	Unit	Source
Stock listed in SET 100	Daily close price	Baht	Bloomberg
Risk free rate	3-month zero coupon bond	%	Thai BMA

Table 1 - List of data

List of stock in SET 100 as of Dec 2019

AAV	BPP	GPSC	MTC	SPRC
ADVANC	BTS	GULF	ORI	STA
AEONTS	CBG	GUNKUL	OSP	STEC
AMATA	CENTEL	HANA	PLANB	SIRI
ANAN	CHG	HMPRO	PRM	SUPER
AOT	CK	INTUCH	PSH	TASCO
AP	CKP	IRPC	PSL	TCAP
AWC	COM7	IVL	PTG	THAI
BANPU	CPALL	JAS	PTT	THANI

BBL	CPF	JMT	PTTEP	TISCO
BCH	CPN	KBANK	PTTGC	TKN
BCP	DELTA	KCE	QH	TMB
BCPG	DTAC	KKP	RATCH	TOA
BDMS	EA	KTB	ROBINS	TOP
BEC	EGCO	KTC	RS	TPIPP
BEM	EPG	LH	SAWAD	TRUE
BGRIM	ERW	MAJOR	SCB	TTW
BH	ESSO	MBK	SCC	TU
BJC	GFPT	MEGA	SGP	TVO
BLAND	GLOBAL	MINT	SPALI	WHA

Table 2- List of Stock

Timeframe and criteria

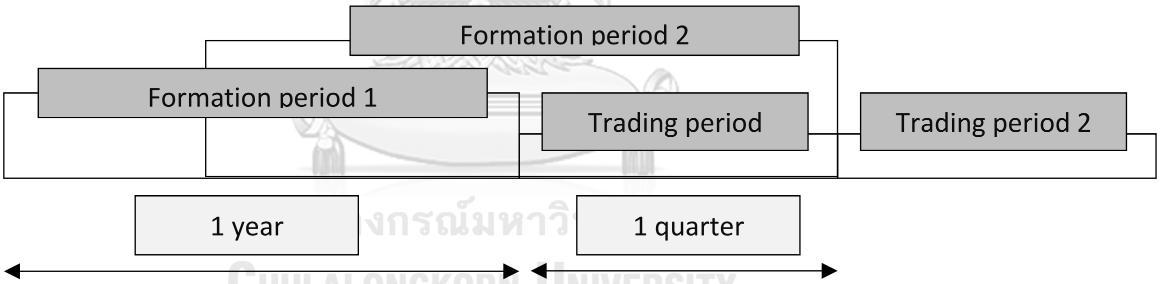

Figure 3- Timeframe

Extra ordinary events' period

As we mentioned about the extra ordinary events period in research hypothesis and conceptual and framework, the period that we define as crisis period will be as follow;

Thailand mega flood July 2011 – November 2011.

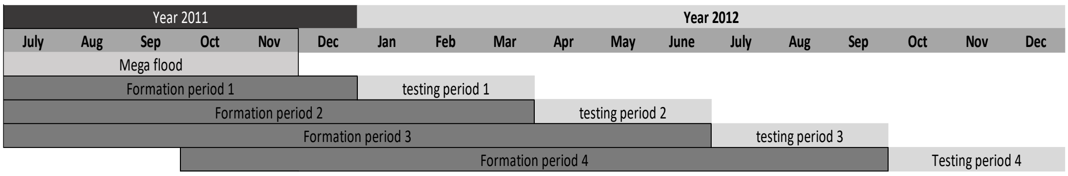

Figure 4- mega flood period

There will be 4 testing period, quarter 1 – quarter 4 in 2012, that use price information from event's period to calculate the correlation.

Political protest October 2013 – May 2014

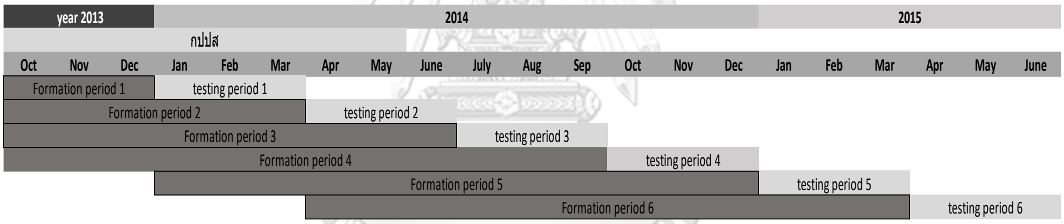

Figure 5- Political protest period

There will be 6 testing period, quarter 1 2014– quarter 2 in 2015, that use price information from event's period to calculate the correlation.

<u>Trading step</u>

1. Use previous daily close price 1 year to calculate dynamic conditional correlation, mean return, average correlation and estimators.
2. Choose pairs that average correlation more than 0.5.
3. Calculate the standard deviation (SD) of correlation for each pair during the

formation period.

4. Use the information from (1) to forecast dynamic correlation at time t+1, t+2, …, t+60.

5. Find pairs that forecasted correlation deviate from its mean below 2 Standard deviation as first cut off.

6. Short stock that previous daily return more than average daily return from the formation periods. Long stock that previous daily return less than average daily return from the formation period. Either short or long need to be identifiable if not no action will be taken

7. Ratio calculation base on relative price between asset if Stock A has higher price than stock B

   Long/short 1 stock for stock A

   Long/short $\frac{stock\ A's\ price}{stock\ B's\ price}$ stock for stock B

8. For the next day after the correlation breakdown, if forecasted correlation falls in a range not below 0.5 SD, no action will be taken. If forecasted correlation falls below 0.5 SD and long short position can identifiable, action will be taken.

9. The 3-month zero coupon bond will be accounted in a day that has no trade action.

4. METHODOLOGY

Step 1: Pair formation

As stock price follows the random walk which means that today's stock price will consist of two elements which are yesterday stock price and random shock. At this step, matching between 2 stocks, stock A will pair with other stock to find the correlation. First, each stocks' daily close price for the previous 1 year used to calculate log return as a formula.

$$R_{i,t} = \ln\left(\frac{P_{i,t}}{P_{i,t-1}}\right) \tag{1}$$

Where $P_{i,t}$ is the price of stock *i* at time *t*. DCC – GARCH model consist of conditional *mean equation* and *variance equation* which can be written as:

$$\text{stock A}: \ R_t^A = A_0 + A_1 R_{t-1}^A + \varepsilon_t^A$$

$$\text{stock B}: \ R_t^B = B_0 + B_1 R_{t-1}^B + \varepsilon_t^B \quad \text{where} \begin{bmatrix} \varepsilon_t^A \\ \varepsilon_t^B \end{bmatrix} \mid I_{t-1} \sim N\,(0, H_t) \tag{2}$$

$$\sigma_{AA,t} = \alpha_A + \beta\sigma_{AA,t-1} + \delta\varepsilon_{A,t-1}^2$$

$$\sigma_{BB,t} = \alpha_B + \beta\sigma_{BB,t-1} + \delta\varepsilon_{B,t-1}^2 \tag{3}$$

A key assumption is that the returns of the individual stock market index are multivariate and normally distributed with zero mean and conditional variance-covariance matrix H_t on the information available at t-1. By that, the multivariate DCC-GARCH model is formally presented as:

$$H_t = D_t R_t D_t = \begin{bmatrix} \sigma_{A,t}^2 & \sigma_{AB,t} \\ \sigma_{AB,t} & \sigma_{B,t}^2 \end{bmatrix} \tag{4}$$

Where;

$$D_t = \begin{bmatrix} \sqrt{\sigma^2_{A,t}} & 0 \\ 0 & \sqrt{\sigma^2_{B,t}} \end{bmatrix} \qquad R_t = \begin{bmatrix} 1 & \rho_{AB,t} \\ \rho_{AB,t} & 1 \end{bmatrix} \tag{5}$$

From equation (5) can implies that

$$\rho_{AB,t} = \frac{\sigma_{AB,t}}{\sqrt{\sigma^2_{A,t}}\sqrt{\sigma^2_{B,t}}} \tag{6}$$

The benefit of the DCC model over others is it can resolve the problem of heteroscedasticity since the estimation of correlation coefficients is based on standardized residuals. Thus, the correlation coefficient derived from a DCC model will alleviate the effect of a parametric impact resulting from variations in volatility.

In DCC, two stages computation are required to get the covariance; first to obtain the conditional variance $\sqrt{\sigma^2_{A,t}}$ by univariate volatility model. The second step is to transform the stock return residual by estimating the standard deviation from the first stage which is $u_{A,t} = \frac{\varepsilon_{A,t}}{\sqrt{\sigma^2_{A,t}}}$. DCC model is

$$Q_t = (1 - \alpha - \beta)\bar{Q} + \alpha u_{t-1}u'_{t-1} + \beta Q_{t-1}$$

$Q_t = (q_{AB,t})$ is time varying covariance matrix of u_t with 2 x 2 dimension.

$\bar{Q} = E\,[u_t u'_t]$ is the unconditional variance matrix of u_t.

α and β are non-negative scalar parameter where $\alpha + \beta < 1$

Scale Q_t to obtain proper matrix of R_t.

$$R_t = \left(Diag(Q_t)\right)^{-\frac{1}{2}} Q_t (Diag(Q_t))^{-\frac{1}{2}} \tag{7}$$

Where $\left(Diag(Q_t)\right)^{-\frac{1}{2}} = Diag\begin{pmatrix} 1/\sqrt{q_{AA,t}} \\ \sqrt{q_{BB,t}} \end{pmatrix}$. By substitute the dynamic process into

$\rho_{12,t} = \frac{q_{AB,t}}{\sqrt{q_{AA,t}}\sqrt{q_{BB,t}}}$ we will obtain

$$\rho_{12,t} = \frac{(1-\alpha-\beta)q_{AB,t}+\alpha u_{t-1}u\prime_{t-1}+\beta q_{AB,t-1}}{\sqrt{(1-\alpha-\beta)q_{AA,t}+\alpha u_{t-1}u\prime_{t-1}+\beta q_{AA,t-1}}\sqrt{(1-\alpha-\beta)q_{BB,t}+\alpha u_{t-1}u\prime_{t-1}+\beta q_{BB,t-1}}} \tag{8}$$

Finally, the pairwise correlation has been formed by the above process.

Step 2: Standard deviation

Find standard deviation of the correlation to use as a threshold for each pair by

$$\sigma_{AB,t} = \sqrt{\frac{1}{n-1}}(\rho_t^{AB} - \overline{\rho^{AB}})$$

Standard deviation will be recalculating every formation period.

Step 3: Pair trading strategy

After finding the pair stock that forecasted correlation deviates more below 2 standard deviation from its mean, position will be opened in the next morning and

close the position in the evening. For the next day after the deviation occurred, if the forecasted correlation still falls below 0.5 SD and both short-long can identifiable then the action will be taken.

Step 4: Return Calculation

In theory, pair trade is market neutral strategy which has a zero initial net investment (long 1 Baht and short 1 Baht). In fact, there still need margin deposit in the brokerage account which is called the margin leverage ratio. By that, daily return is calculated by divided the profit and loss with the margin ratio. Previous research done by Gatev et al. (2006) use 2:1, Avellaneda and Lee (2010) use 4:1 leverage. In this paper, we assume a 2:1 leverage ratio. We compute the daily return on actual employed capital.

$$daily\ return = \frac{daily\ net\ Profit\ and\ Loss}{Trade\ value} \tag{9}$$

Step 5: Performance evaluation

In order to evaluate Pair Trading's performance, one of the approaches is to calculate portfolio excess returns which consist of all trading pair by subtracting the risk-free rate from the yearly return series. According to Bartholdy and Peare (2005) concluded that the small gain from using Fama French Model in terms of explanatory time does not justify the work involved in calculating two more factors. By that we decided to regress the portfolio excess return series on CAPM:

$$R_t^p - R_t^f = \alpha_t^p + \beta_t^p\left(R_t^m - R_t^f\right) + \varepsilon_t^p \tag{10}$$

Where R_t^p is the portfolio return, R_t^f is risk free rate, R_t^m is market return (SET Index). ε_t^p is the error term and α_t^p, β_t^p are regression parameters, α_t^p measures the average abnormal return. To test statistical significance of abnormal returns (AR), we conducted a hypothesis test with the following null and alternative hypothesis:

$$H_0 : \alpha = 0 \quad H_a: \alpha > 0$$

5. EMPIRICAL RESULTS AND DISCUSSION

5.1 Correlation Distribution

According to the mean correlation distribution for each formation period, the mean correlation among stocks listed in SET100 fall in the range of 0.1 to 0.3 which considered as negligible correlation.

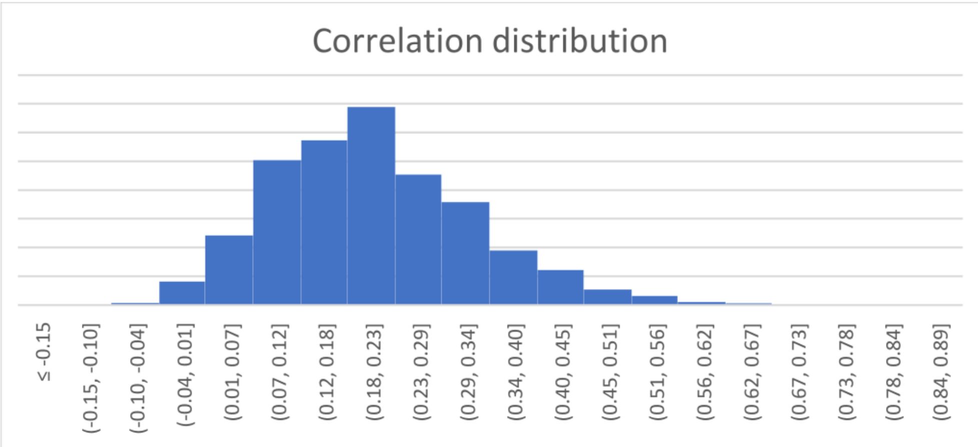

Figure 6-Correlation Distribution

We also test the correlation distribution for each formations and found that during the year 2011 – 2014 where Thailand face extra ordinary events, at 95 percentiles mean correlation is around 0.4x - 0.5x for each formations. But, 2015 – 2019 mean correlation at 95 percentiles only at 0.3x which considered as low positive correlation as the interpretation table below.

Size of correlation	Interpretation
0.0 - 0.3	negligible correlation
0.3 - 0.5	Low positive correlation
0.5 - 0.7	Moderate positive correlation
0.7 - 0.9	High positive correlation
0.9 - 1.0	Very high positive correlation

Table 3 : Correlation Interpretation, Mukaka, MM (2012) who studied a guide to appropriate use of Correlation coefficient in medical research and Hinkle DE, Wiersma W, Jurs SG (2003) which studied about Applied Statistics for the Behavioral Sciences.

From 2011-2019 for each formation period, the mean correlation for each pair fall in the range of 0.1 to 0.3 and there were few pairs fall above 0.5 (Appendix 1) which means that on average stocks listed in SET 100 are traded on low to moderate positive correlation. For pair trading, the more correlated the better because we believe that stock that on average move in the same direction once the deviation has taken place they should come back to move in the same direction as usual. By that, this paper filtered out pairs that mean correlation from the formation period fall below 0.5 to select only moderate to highly correlated pair. 0.5 is not too low nor too high as it was around 95 percentiles for each formations even that there were some formations that 0.5 was around 99 percentiles. But, as pair trade rely on the highly correlated pair, by choosing pairs that low correlation is not appropriate as it's not move in the same direction. The studied period cover 2 extra ordinary events which are mega flood in 2011 and political protest in 2013-2014, during that period stock seems to move in the same direction which result in higher number of correlated pairs for next following year. See Appendix 1, 2012 was the year that had the highest number of correlated pairs falls above 0.5. This result consistence with the previous research done by Isogai that during the crisis period correlation among assets seem to be more intense.

5.2 Result from implementation of pair trade

Year	Profit	Loss	Net
2011	21	29	-8
2012	109	64	45
2013	21	26	-5
2014	116	63	53
2015	10	3	7
2016	10	9	1
2017	4	5	-1
2018	3	1	2
2019	12	10	2

Table 4 Win Vs Loss pairs from 40 testing period

From the table above, 2011 and 2013, where Thailand encountered mega flood and political issues, the stock movement seems to reflect the situation in the same direction which short-long strategy not work in this circumstance because this strategy required one stock to go up and one to go down. As stocks seem to move in the same direction, pair stocks in the mentioned trading period result in higher loss pairs than win pairs. However, as price seems to move in the same direction than usual, therefore, using 2011 and 2013 prices to form pairs can generate a higher number of correlated pair to trade in year 2012 and 2014 compare to other years. There were 532 pairs from 40 testing period during 2011-2019 which divided to 305 win pairs and 227 loss pair, the percentage of win ratio accounted around 57% which significant at 1% significant level. Furthermore, as a daily trade, among 774 days where trade acion has been taken, the percentage of win ratio accounted around 52% which significant at 10% significant level.

Proportion test	Model 1	Model 2
Number of OBS	532	774
Mean	0.5733	0.5232
Standard deviation	0.021	0.02
Pr (Z>z)	0.0004***	0.0978*

*** p<0.01, ** p<0.05, * p<0.1

Also, we find that over 40 testing periods, there were few pairs that traded in many testing period and result in net gain. As the table below, number in total column show number of testing period that the pair has been executed and win column show win times. This table contained 36 pairs that most appeared in the trade action with more than 50% to win. SCB and KKP which listed in the same industry showed up with highest number of total trade with 50% to win.

Pairs	total	WIN	%
SCB_KKP	14	7	50%
STA_SCC	10	6	60%
ROBINS_GLOBAL	9	7	78%
IRPC_BBL	7	5	71%
SPRC_BCP	6	3	50%
SCC_PTT	6	3	50%
PSKBANK	6	4	67%
SGP_BANPU	5	3	60%
BBL_AMATA	5	3	60%
IVL_BCP	5	3	60%
KBANK_IRPC	4	2	50%
INTUCADVANC	4	2	50%
TCAP_PSH	4	2	50%
SIRI_PSH	4	2	50%
TOP_PTTEP	4	2	50%
TOP_SCB	4	3	75%
TRUE_AP	4	3	75%
TCAP_SCB	4	3	75%
QPTT	4	3	75%
SIRI_KTB	4	4	100%
PSCPN	3	2	67%
KTB_BANPU	3	2	67%
STEC_SCB	3	2	67%
STEC_CK	3	2	67%
TRUE_GUNKUL	3	2	67%
QKTB	3	2	67%
TMB_BCP	3	2	67%
ROBINS_HMPRO	3	2	67%

GLOBAL_BJC	3	2	67%
TRUE_CPN	3	2	67%
TMB_SCC	3	3	100%
PTT_MINT	3	3	100%
TMB_KTB	3	3	100%
TCAP_QH	3	3	100%
HMPRO_CK	3	3	100%
TMB_KBANK	3	3	100%

Table 5 Pair stock

Not only SCB and KKP but TMB and KBANK has been executed by using this strategy and generate the profit everytimes. Not only within the same indusry, there were many stocks that paired with another stock in difference industry which provided 100% chance to win such as SIRI and KTB or PTT and MINT. In conclusion, by using Dynamic Conditional Correlation to form pairs can generate the higher number of winning pair than losing pair.

An abnormal return

	Model 1
VARIABLES	Q1-Q4
Rm-Rf	-0.0141
	(0.0212)
Constant	0.000135
	(0.000197)
Observations	2,182

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Model (1) calculated from the period 2011-2019 which include the period where 2 extraordinary events occurred, and which abnormal return has not been found. As mentioned before, when there is a crisis stock price seems to reflect the situation in the same direction and result in a net loss by using this strategy. When 2 extraordinary events were excluded from the testing period, we found a higher abnormal return but still not significant. As this strategy can generate higher number of winning pairs than losing pairs, we then tested the daily return propotion by each quarters. The result showed that among 4 quarters, quarter 1 result in net loss and the winning ratio accounted less than 50% where others higher than 50%. Only quarter 2 and 4 that winning ratio more than 50% which significant at 10% significant level. By excluding quarter 1 where winning ratio less than 50%, we found the positive abnormal return around 0.04% per day or 15% annaulized return with 10% significant level. Also, if this strategy has been only executed in quarter 2 and quarter 4, this strategy can generate an abnormal return around 0.06% per day or 25% annualized return with 5% significant level.

Proportion test	Quarter 1	Quarter 2	Quarter 3	Quarter 4
Number of OBS	199	215	185	175
Mean	0.47	0.55	0.51	0.56
Standard deviation	0.04	0.03	0.04	0.04
Pr (Z>z)	0.782	0.055*	0.412	0.056*

*** p<0.01, ** p<0.05, * p<0.1

VARIABLES	Model 2 Q2-Q4	Model 3 Q2 and Q4
Rm-Rf	-0.003	-0.015
	(0.0241)	(0.0332)
Constant	0.000395*	0.000614**
	(0.00023)	(0.000303)
Observations	1,628	1,067

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

In conclusion, this strategy can generate an abnormal return in specific period. As the result showed if this strategy has been excuted only in quarter 2 and quarter 4, this strategy can generate a significant abnormal return. Furthermore, we focused on 2 extraordinary events period whether using this strategy can generate higher abnormal return than normal period. The result from proportion of wining ratio accounted more than 50% with 5% significant level as the table showed below

Proportion test	Events
Number of OBS	384
Mean	0.55
Standard deviation	0.03
Pr (Z>z)	0.021**

*** p<0.01, ** p<0.05, * p<0.1

We use dummy variable to indicate trading days that using price information from the period where the extraordinary events occurred.

$$R_t^p - R_t^f = \alpha_t^p + \beta_t^p\left(R_t^m - R_t^f\right) + \alpha_{2,t}^p d_{event} + \beta_{2,t}^p\left(R_t^m - R_t^f\right) d_{event} + \varepsilon_t^p$$

d_{event} is a dummy variable denote as 1 if that testing period use price information from extraordinary events to form pair.

α_2 capture the difference between abnormal return from event period and normal period.

VARIABLES	Model 4
Rm-Rf	-0.00242
	(0.0238)
Constant-Event	0.000916**
	(0.000440)
Beta-Event	-0.0634
	(0.0523)
Constant	-0.000110
	(0.000232)
Observations	2,182

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

The result of model 1 indicate that the abnormal return in trading period next to the extraordinary events has been found around 0.09% per day or 39% annualized return higher than normal period with 5% significant level. This result seems to consistence with previous research done by Isogai as stock seems to be more correlated to each others in crisis than normal period.

6.CONCLUSION

Pair trading concept using in this research paper remained likely the same as Morgan Stanley's concept in 1980s that is to long an underperforming stock and short an overperforming stock at the same time, but adding a new way to find the trading pairs, so investors are able to enjoy 2-way price spread. This research paper adopted the standard deviation method in order to capture the deviated pair by using below 2 SD rule to indicate the action whether trade or not trade. This paper mainly focused on Dynamic Conditional Correlation where correlation is not constant overtime, with correlation change day by day, we can find the deviated pairs to trade. With the experimental result, this strategy not performed well throughout the year but did perform well in specific periods as discussed in the empirical result section. If using price information from extra ordinary event' period, this strategy can generate up to 39% annualized return higher than normal period. This study finds the evidence that abnormal return still exists in stock exchange of Thailand. However, as mentioned this strategy may not work well throughout the year since there may have other external factors that affect the stock price which past stock movement cannot capture such as fund flow, size of the stock or quarter effect. The finding obtained in this paper still has many factors to study in future research including but not limited to the effect of different stock sizes in pair trade and also fund flow effects on stock movement.

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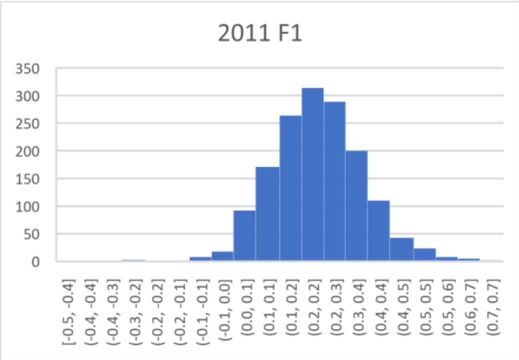
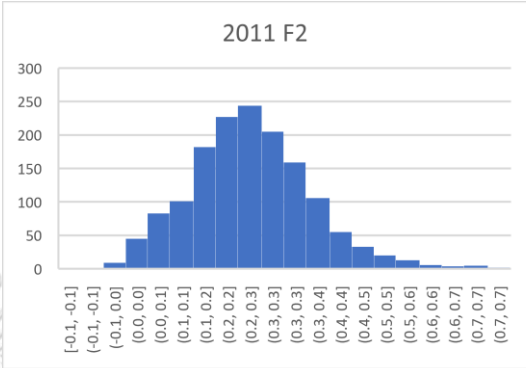
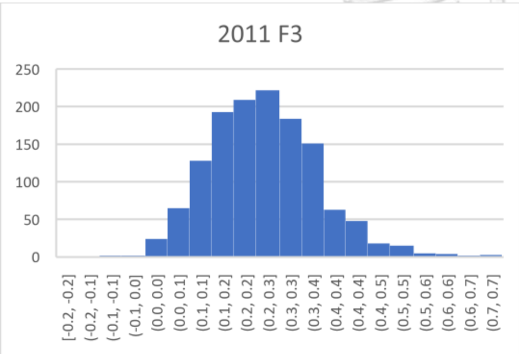
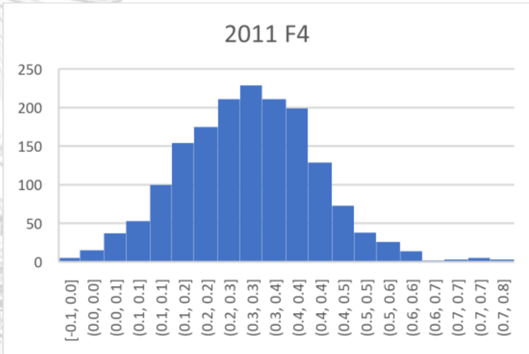
Appendix 1

2011 Correlation distribution

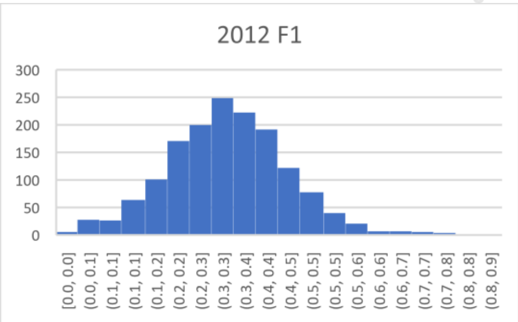


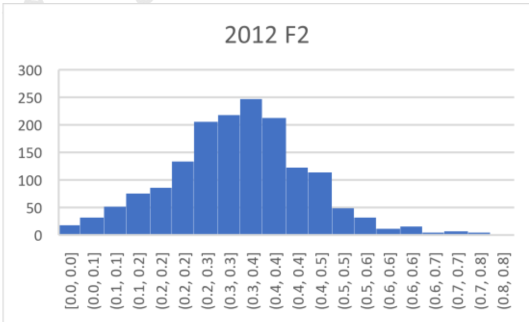


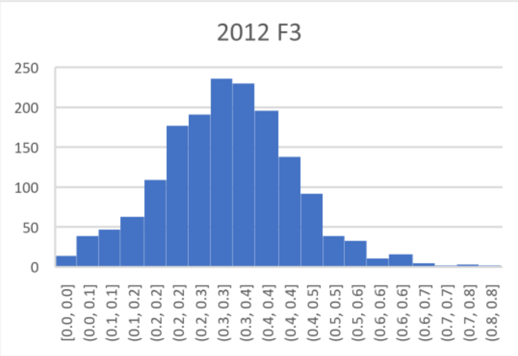


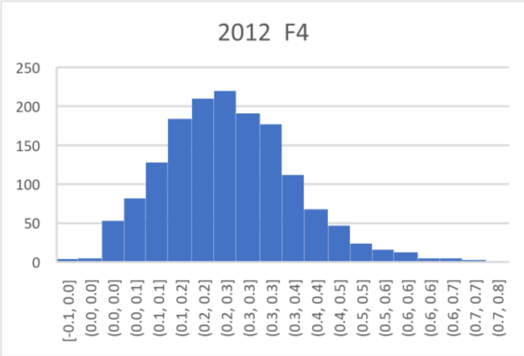


2012 Correlation distribution

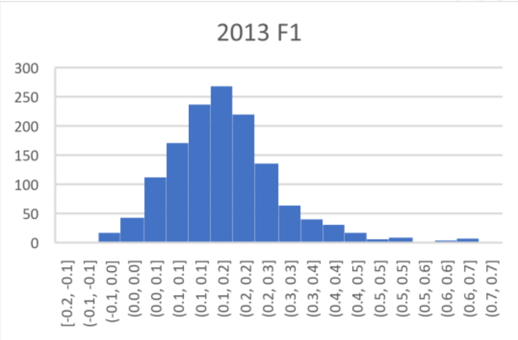


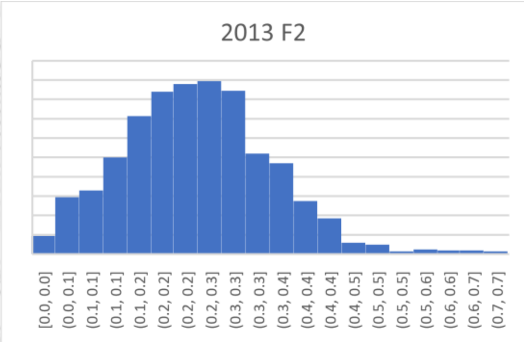


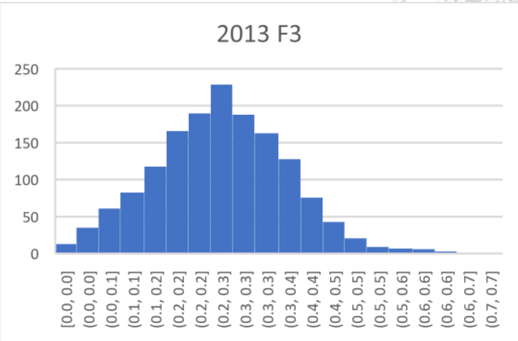


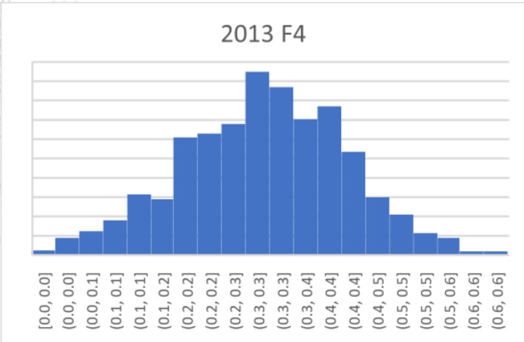


2013 Correlation distribution

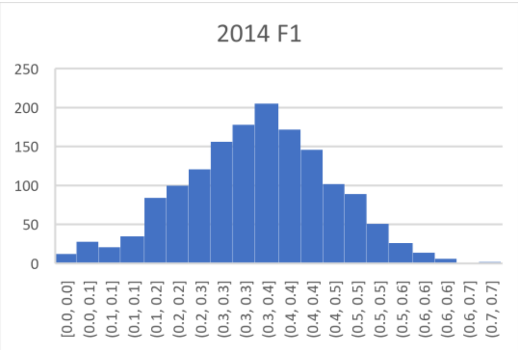


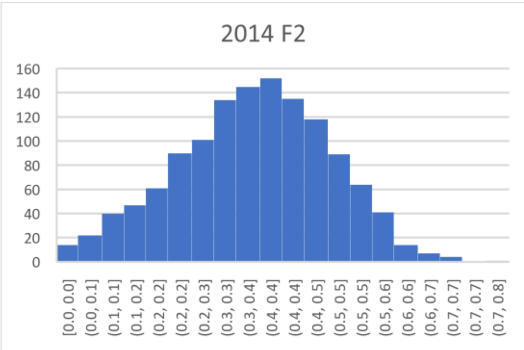


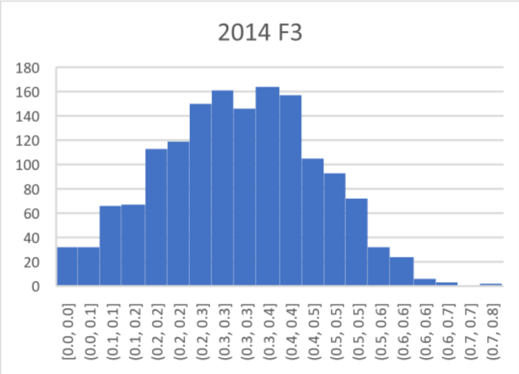


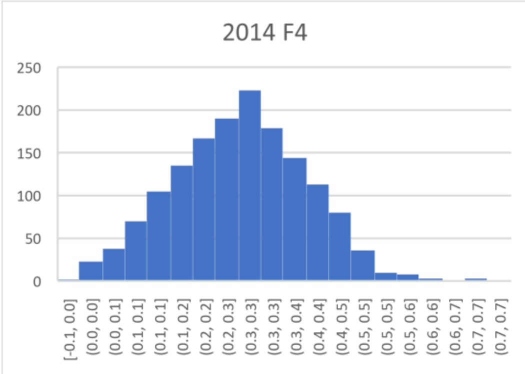


2014 Correlation distribution

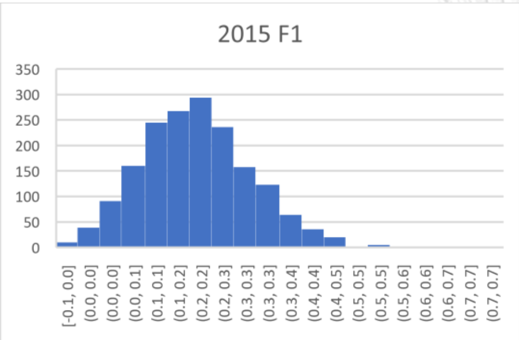


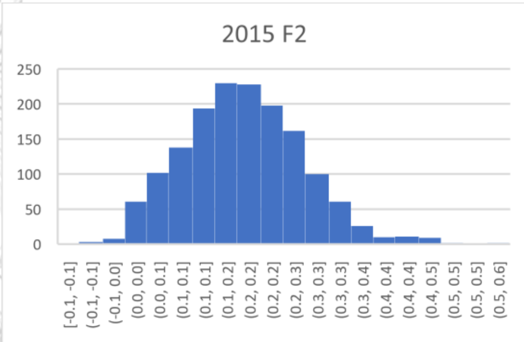


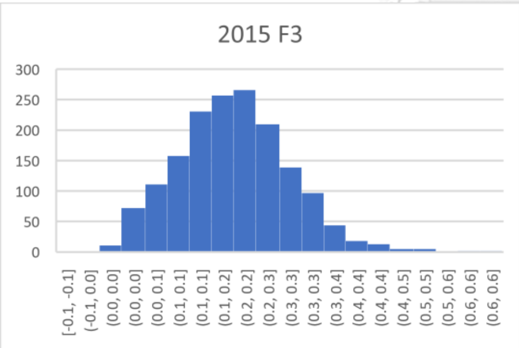


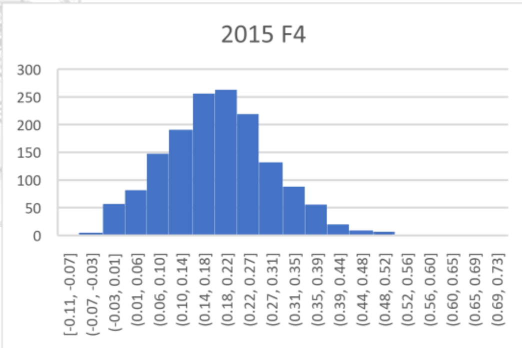


2015 Correlation distribution

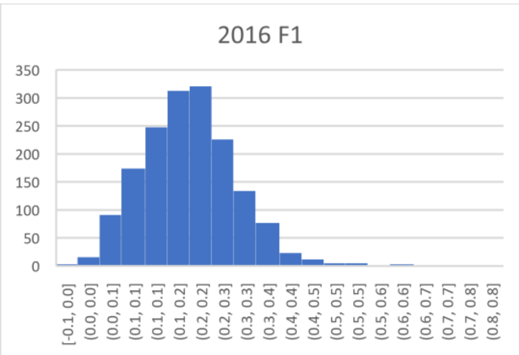


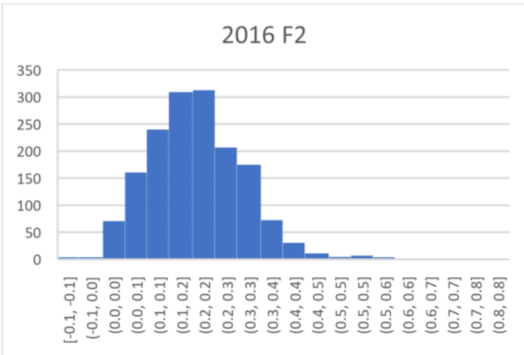


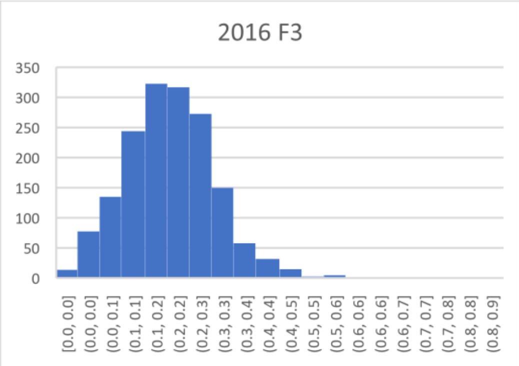


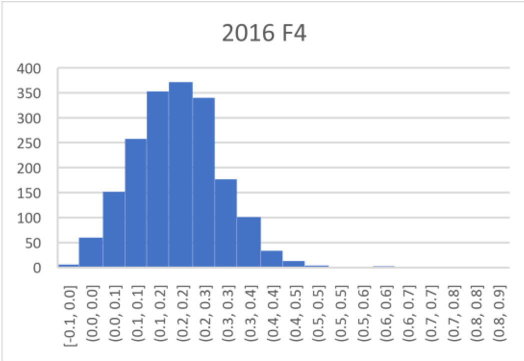


2016 Correlation Distribution

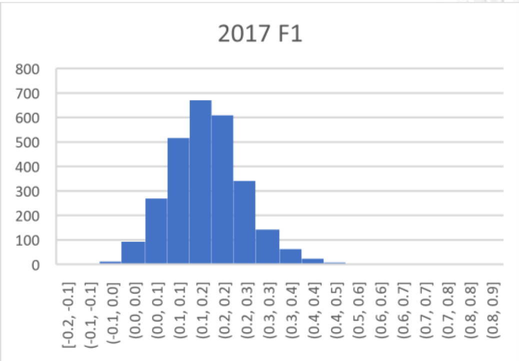


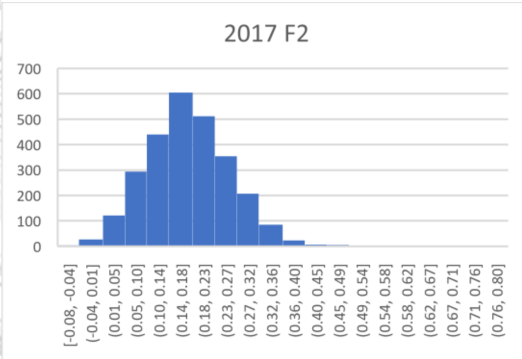


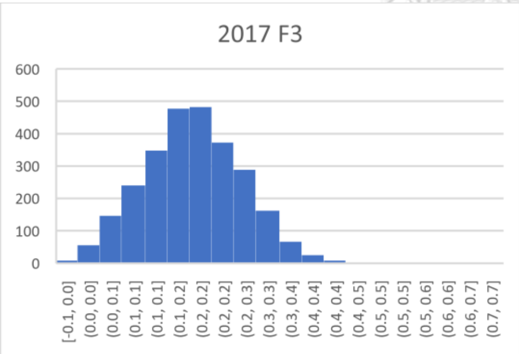


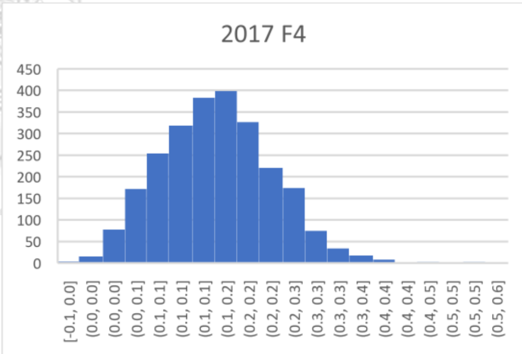


2017 Correlation Distribution

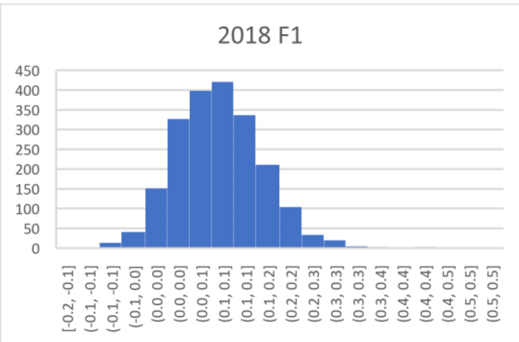


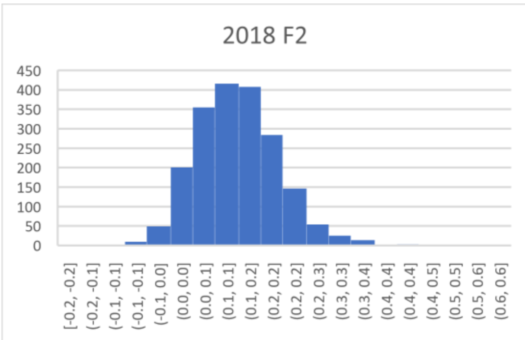


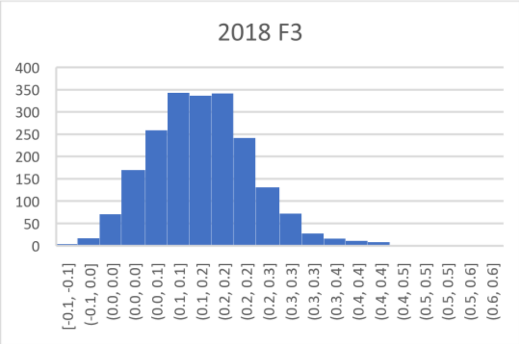


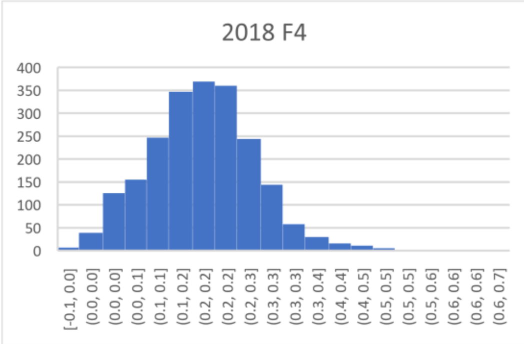


2018 Correlation distribution

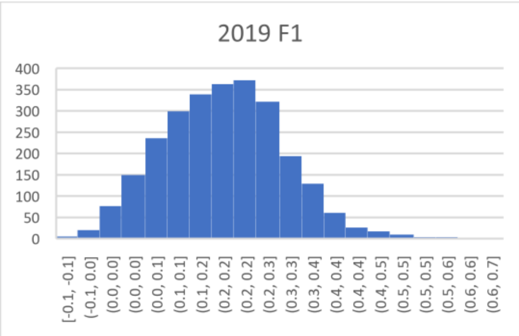


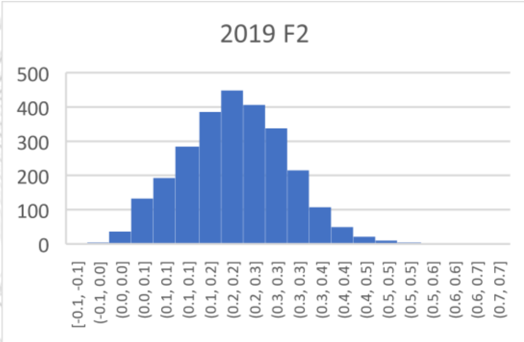


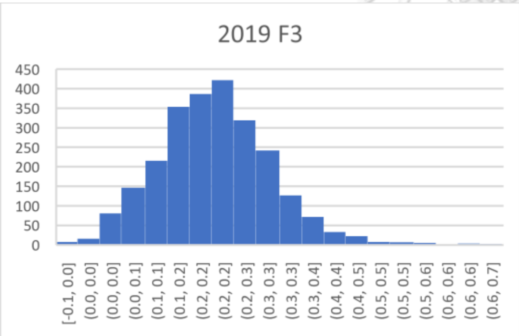


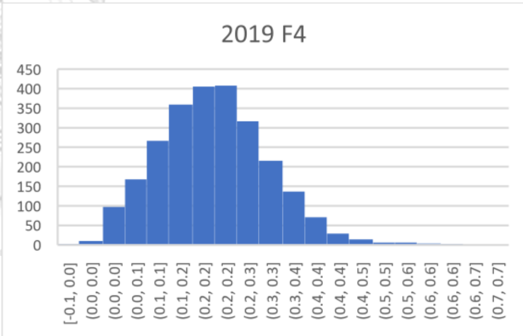


2019 Correlation distribution









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