Project CIRP--Inflation Theory with Cryptocurrency/ Falling Knife
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Objective - Inflation Theory with Cryptocurrency

The objective of the CIRP project is mainly focused on arbitrage signals. However, the background of economy and inflation trends play an important role in the volatility of prices. Therefore, for the deeper research of what effects will inflation produce and how it will change or influence the trends of cryptocurrency, I do the analysis based on Garch models to find the relationship between inflation and returns to volatility of cryptocurrency. Compared with other currency markets, cryptocurrency is a capital pool which means that each cryptocurrency affects each other. Therefore, the whole analysis also puts whether a strong connection and cointegration relationship exists in the prices into consideration.

Phase one - the purpose of the project
For the project I have several questions to handle: 1) What is the volatility of cryptocurrency? 2) What hypothesis do I need to test? 3)What model do I need to do the analysis of time series? 4) What is the result of the relationship between the tested return of cryptocurrency and inflation?

Phase two - the organization of the project
To be more clear of the relationship, firstly, the feature of cryptocurrency is necessary. We should get into the cryptocurrency market and choose four main cryptocurrencies to do the comparison and analysis. After knowing the features of objects we can insert **several hypotheses** and data to test their truth. Based on these hypotheses, we could design models for the research. In my point of view, **GARCH models** are the main tools. To thoroughly reveal the relationship, I'd like to escalate extensive GARCH analysis based on detailed **AR-GARCH**, **TGARCH** and **EGARCH models**. As a comparison test hypothesis I use three related models named **AR-GARCH-M**, **TGARCH-M** and **EGARCH-M.** The difference in the cryptocurrency market is that there are several types of currencies available in the market. Therefore, the cointegrating relationships based on Johansen maximum likelihood test among cryptocurrency prices are also in the procedure.

The remaining sections are related to 2.the details of theoretical framework and hypotheses 3.employed methodology 4.details of descriptive statistics of four kinds of price samples 5.outcomes of analysis and results.

2.2 returns and volatility

Based on Friedman-Ball hypothesis: the inflation uncertainty reduces the efficiency of the prices system in economic activity. Therefore, the signal about price relative to inflation is hard to predict. Due to the uncertainty of the inflation trend and returns I set there is an asymmetric relationship between them. About more details of the relationship we need to compare other hypotheses such as: **inflation increases improve inflation forecasts** and **losses of returns have a better or huger influence on volatilities** and lastly **a rise of uncertainty in inflation may go an opposite future inflation trend**.

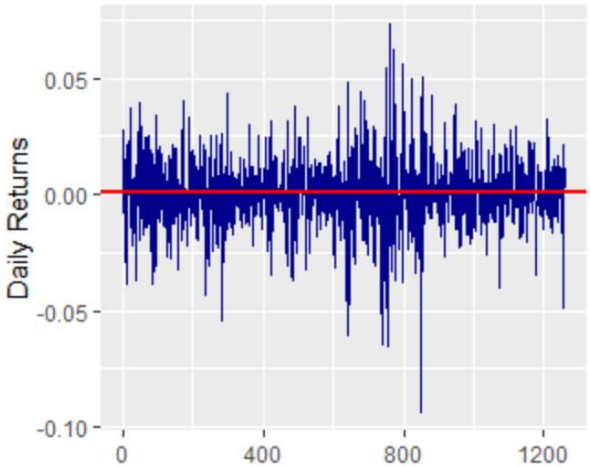
Based on the researches listed above I formed several hypotheses:

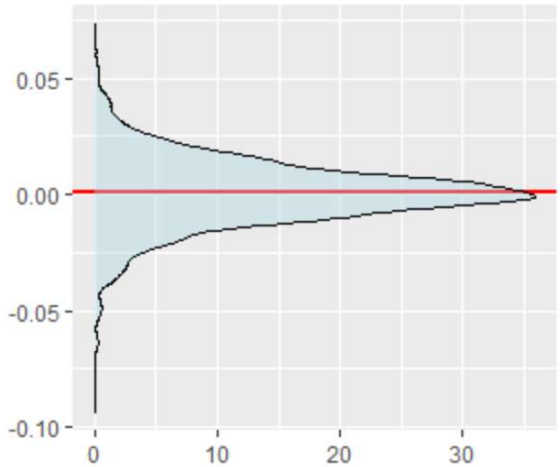
1. A rise in the returns of cryptocurrency i has an uncertainty relationship with the returns of cryptocurrency j.
2. The relationship between returns and volatilities is asymmetric.
3. A down in volatility is a trend of downing in returns.

2.3 Methodology

Compare the data of cryptocurrency returns with periods of high volatility. This implies that our returns series should be seen as conditionally heteroskedastic, a condition in which the variance of the residual term, or error term, in a regression model varies widely. We could consider the returns changing in a systematic way. For all, firstly using ARCH/GARCH approach in modeling the process of relationship through returns and volatility. And test it based on the mean model. And then test all of my hypotheses listed above based on MGARCH and EGARCH models. Finally, get the probability result or the correlation coefficient between inflation and currency based on MIDAS.

2.4 descriptive analysis





Make a visualization of the sequence of returns, based on the graph we know that the mean is around 0 and fluctuate around the 0 which means that it does not have a clear trend, divergence

or pitch. The kurtosis distribution graph shows that it is a dentistry function with thicker flanks on both sides named Leptokurtic.

When solving the Pearson correlation coefficient between all the four returns series, we could find that the 1% level is significant and shows that it has positive correlation between the series. Comparing 6 groups of data we get the final conclusion that the strongest correlation is based on Bitcoin and Litecoin. And also this result is successfully accepted by the one lag test with the 5% level. Through the whole test and finding the strongest correlation between which currencies, we also could know that all of the returns are contemporaneous.

Then the ARCH LM test is necessary for the verification. I use this test to determine the most efficient model in the first lag because from high-level to low-level, all of the probabilities are higher than 0.05 which means that it opposes the original hypothesis. After that we get the conclusion that all the cryptocurrencies have ARCH effects in the first order. And then we could use the GARCH models to model the volatility of four currencies.

The application of the AR-GARCH(1,1), EGARCH and TGARCH, I used two different factors to ensure the isolation of each. And then the work is based on whether returns affect the volatility Of cryptocurrency. Firstly, testing the returns of four currencies are jointly significant. And then list one of them out of the considering objective and compare how the other three currencies affect the separate one. Therefore, we could know GARCH models are available for all Friedman-Ball hypotheses except EGARCH-M. For Litecoin it is suitable in both GARCH and specific TGARCH. For Ripple it supports under the lag of 1%.

2.5 MIDAS model

Finished all of the unit root tests and stationarity tests. The fluctuation of data is suitable for the following analysis. Therefore, I will use MIDAS to finish the final probability test. **A MIDAS regression** is a direct forecasting tool which can relate future low-frequency data with current and lagged high-frequency indicators, and yield different forecasting models for each forecast horizon. It can flexibly deal with data sampled at different frequencies and provide a direct forecast of the low-frequency variable. It incorporates each individual high-frequency data in the regression, which solves the problems of losing potentially useful information and including mis-specification.
The most important advantage of the GARCH-MIDAS model is that it allows us to link the daily observations on cryptocurrency returns with macroeconomic variables, sampled at lower frequencies, in order to examine directly the macroeconomic variables' impact on the cryptocurrency volatility. Inflation volatility and return of cryptocurrency are two important factors I will put into consideration.

From the **least squares** equation, we could know the three estimates of the probability of BTC is 0.000; the probability of ETH is 0.0195; the probability of Litecoin is 0.8680; the probability of Ripple is 0.817. It says that the inflation volatility ratio is a good point to estimate the fluctuation of Litecoin and Ripple. And also based on the **MIDAS equation**. My inflation period is monthly and the price of cryptocurrency is daily; therefore, the inflation is in the first pacification box and each cryptocurrency is a higher frequency regressor. Each probability indicates that BTC is not a closely related prediction variable for forecasting the trend of inflation.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.002467	0.001784	1.382975	0.1678
BTC(-1)	-0.066582	0.059098	-1.126638	0.2609
INF\INFLATION(-1)	-0.000312	0.000719	-0.434308	0.6644

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.012577	0.005496	2.288503	0.0228
ETH(-1)	0.125247	0.053331	2.348471	0.0195
INF\INFLATION(-1)	-0.000221	0.002198	-0.100573	0.9200

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.000694	0.002029	0.341851	0.7327
LIT(-1)	0.009835	0.059102	0.166409	0.8680
INF\INFLATION(-1)	-0.000582	0.000820	-0.709897	0.4784

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.014306	0.007088	-2.018291	0.0445
RIP(-1)	-0.014297	0.059649	-0.239694	0.8107
INF\INFLATION	0.000160	0.002829	0.056436	0.9550

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.174296	0.178397	0.977013	0.3295
INFLATION(-1)	-0.081028	0.061771	-1.311742	0.1909

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.148449	0.181423	0.818246	0.4140
INFLATION(-1)	-0.048919	0.062425	-0.783637	0.4340

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.134214	0.160883	0.834235	0.4049
INFLATION(-1)	-0.046351	0.061909	-0.748695	0.4547

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.160513	0.170643	0.940637	0.3478
INFLATION(-1)	-0.045025	0.063469	-0.709408	0.4787

Phase three - Conclusion

Based on inflation theory, how's the relationship of returns and volatilities of cryptocurrency. I tested that there are two different connections between inflation and cryptocurrencies. From the least squares test the independent objective is inflation ratio and then we test the relationship with cryptocurrencies of Bitcoin, Ethereum, Litecoin and Ripple. We could find clearly that the fluctuation of inflation has seldom affected the return of Bitcoin and Ethereum due to the probability of 26% and 1.95%. Compared with Litecoin and Ripple the inflation fluctuation is a very important and obvious signal for testing the trend of them. Therefore, we could analyze features of inflation based on the change of Litecoin and Ripple. Also we could know that in the cryptocurrency market it has a cointegration relationship contrasted with other currency markets. Therefore, in the opposite direction of analysis. When we want to explore whether cryptocurrency movements are influenced by inflation. Based on the MIDAS test, cryptocurrency works as an independent variable. We could find fresh correlations between cryptocurrency and inflation shown above: BTC and ETH is not a good choice to be a fluctuation hint of inflation. However, Litecoin and Ripple are related. Think of cause and effect in the opposite direction, inflation fluctuations would not produce obvious effects to bitcoin.

For the development of the project, it is a good point to do some detailed analysis based on inflation and cryptocurrency. We could combine these correlations with more variables such as paper currency, exchange rate, economy and policy. All of them are helpful to find a more complicated and complete model to test the trends of cryptocurrency and find arbitrage opportunities of the trading.

Objective - Falling Knife

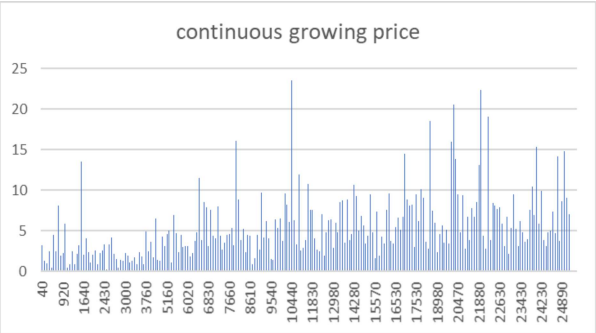
Over the past decades with the development of the securities financial market, stock indexes have become a relatively mature investment tool in the market with its advantages in hedging, price discovery and risk management. Therefore, for most investors to effectively avoid the risk in the stock index futures investment is a matter of great concern. This article uses the continuous rising and falling characteristics of high-frequency data of stock index futures as the project object, and computes the relationships based on time and quantity respectively.
For detecting the risk management of the probability. This article starts with the one-minute and ten years rate of return of the monthly continuous index of the S&P 500 index futures. The continuous rising and falling minutes and fields will be the most important information

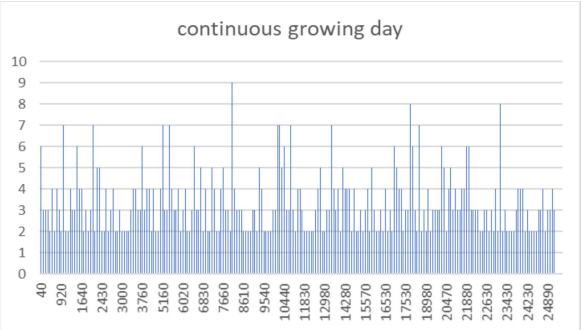
Phase one - the purpose of my project

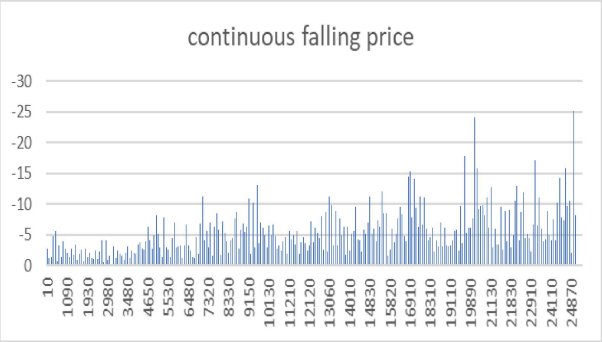
Introduce the main methods and steps of survival analysis and then introduce the related theory of the ACD model, which includes the properties and parameter estimation methods of the linear and nonlinear ACD models, and then use the relevant theory and parameter estimation of the Copula model to study the continuous rise and fall of stock prices. Mostly, find a

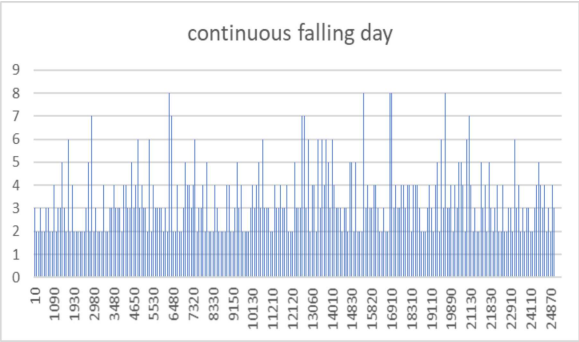
Phase two - the organization of the project

Copula-TACD model





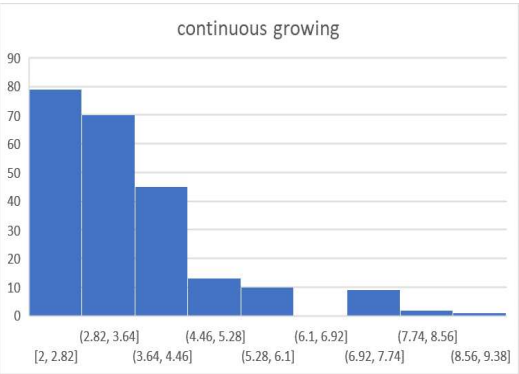


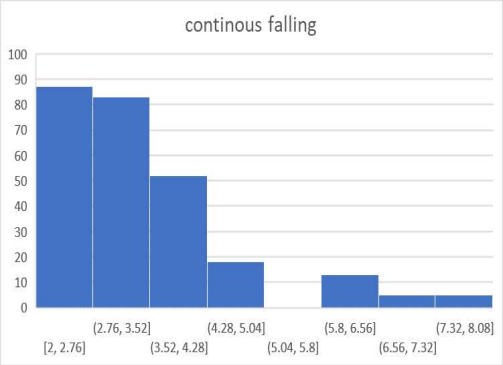


As shown in the figure, the charts of consecutive gains and consecutive losses are similar, and the charts of consecutive growing times and consecutive losing times are similar. There is a certain degree of aggregation in the consecutive gains and losses, but the regularity between time is not strong. Therefore, time and benefits are studied using different models.

Research on the time of consecutive ups and downs:
Using descriptive statistics on the time of consecutive rising and falling every day in the past ten years, the data shows that the average value of the time series of continuous rising and falling is about 3.32 days, the median standard deviation and other data are close, and the kurtosis skewness of the continuous rising time is slightly higher than the consecutive decline time, which is in line with the market trend. The standard deviations are lower than the mean, indicating that there is no overdispersion in time and the time series tends to be stationary.

	Mean	Median	Std. Dev.	Skewness	Kurtosis	ADF test	Prob. *
Growing	3.323144	3	1.458944	1.352296	4.63302	-14.10272	0.000
Falling	3.323194	3	1.389064	1.292627	4.522026	-11.30982	0.000





The autocorrelation diagrams of the two series show that the autocorrelation of the continuous rise and fall is weak, and the lag first-order autocorrelation coefficient of the two series is not significant, indicating that the continuous rise time of the previous period is not closely related to

the time of the next period which means that there is no significant effect. What's more, under the larger lag order there is a weak autocorrelation in the time of consecutive ups and downs.

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.070	0.070	1.1304	0.288
		2	0.002	-0.002	1.1319	0.568
		3	0.076	0.077	2.4980	0.476
		4	-0.023	-0.034	2.6266	0.622
		5	-0.055	-0.051	3.3313	0.649
		6	-0.034	-0.034	3.6122	0.729
		7	-0.035	-0.027	3.9095	0.790
		8	-0.018	-0.006	3.9863	0.858
		9	-0.019	-0.015	4.0714	0.907
		10	0.049	0.053	4.6631	0.913
		11	-0.108	-0.120	7.4695	0.760
		12	-0.060	-0.047	8.3591	0.756
		13	0.017	0.012	8.4304	0.814
		14	-0.074	-0.062	9.7868	0.778
		15	-0.091	-0.078	11.822	0.692
		16	-0.061	-0.067	12.734	0.692

Growing

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.044	0.044	0.5234	0.469
		2	0.086	0.084	2.4842	0.289
		3	0.013	0.006	2.5295	0.470
		4	0.015	0.007	2.5882	0.629
		5	-0.064	-0.067	3.6900	0.595
		6	-0.017	-0.013	3.7647	0.708
		7	0.041	0.053	4.2126	0.755
		8	-0.052	-0.053	4.9511	0.763
		9	0.043	0.043	5.4680	0.792
		10	0.043	0.044	5.9820	0.817
		11	0.073	0.061	7.4681	0.760
		12	0.139	0.136	12.839	0.381
		13	0.087	0.060	14.939	0.311
		14	0.053	0.027	15.724	0.331
		15	-0.053	-0.062	16.507	0.349
		16	-0.067	-0.077	17.792	0.336

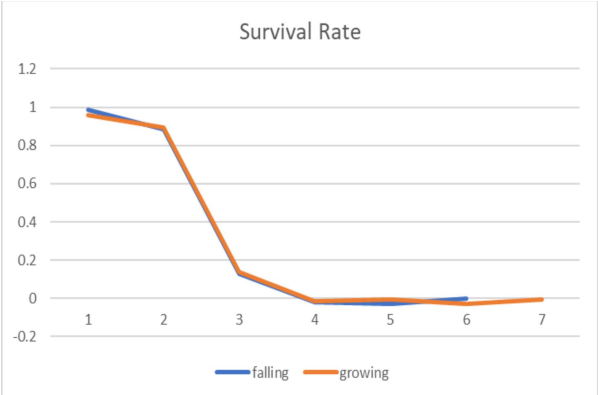
falling

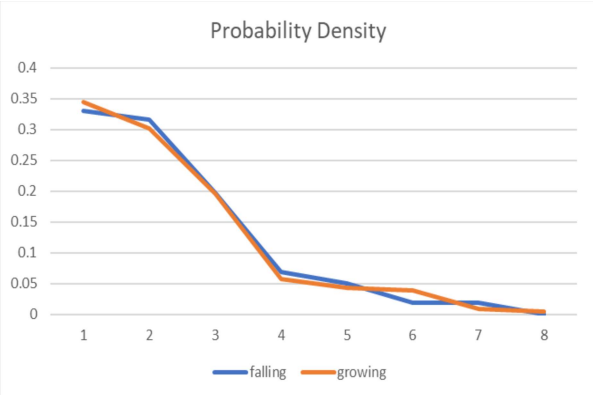
The total number of consecutive ups and downs in the sample interval is denoted as N, and the segments with consecutive ups and downs days greater than or equal to t days are denoted as A_g(t) and A_f(t) The probability estimates are denoted as:

$$S_g(t) = P_r(T \geq t) = \frac{A_g(t)}{N}$$

$$S_f(t) = P(T \geq t) = \frac{A_f(t)}{N}$$

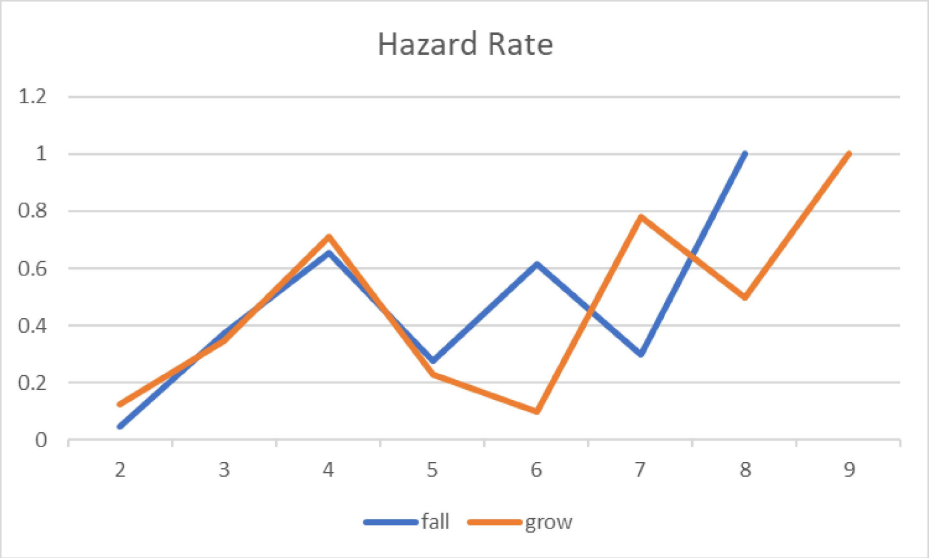
The probability density function shows that the continuous rise and fall density curve is still relatively close. When the continuous rise and fall time is short, the probability value of each time period is relatively large. With the increase of the number of consecutive rise days, the probability decreases significantly. When it exceeds seven days, it is basically the same as the horizontal axis. Coincidence, it is difficult to maintain a consistent state for more than seven days, and the stock and stock index markets fluctuate in the same direction in a short period of time.





Hazard Rate

The overall picture shows that the hazard rate function of the continuous rise and fall time is not much different from the four-day continuous rise time and the hazard rate function of the continuous fall time, the functions basically overlap and the hazard rate is low. And most of the hazard rate curves for the number of consecutive rising and falling days are lower than 0.5, indicating that it can be held for a long time and there will not be too much difference in the number of positive and negative feedback days. This is instructive for stock holdings and can be used as a risk assessment criterion. Time to close trades according to risk tolerance preference.



For the descriptive statistics of the time of continuous rise and fall, four characteristics are summarized: **1. Weak autocorrelation has almost no autocorrelation in the low-order lag period; 2. The discreteness is not strong; 3. Does not meet the common probability distribution; 4. No regularity.**

Research on the price of consecutive ups and downs:

The descriptive statistical results of the consecutive gains and losses data show that the median standard deviation values of the consecutive gains and losses series are similar, and the average gains of the gains and losses are slightly higher than the average gains of the losses, but the gains of the gains and losses have a higher peak. degree and skewness, which means that there are more outliers in the return of the continuous decline, and the return of the continuous decline has a steeper peak and thicker tail than the return of the continuous increase. Falls do not have strong discreteness. The mean value of the ADF statistic is significantly less than 0.01, so the series of consecutive rising and falling returns are all stable time series.

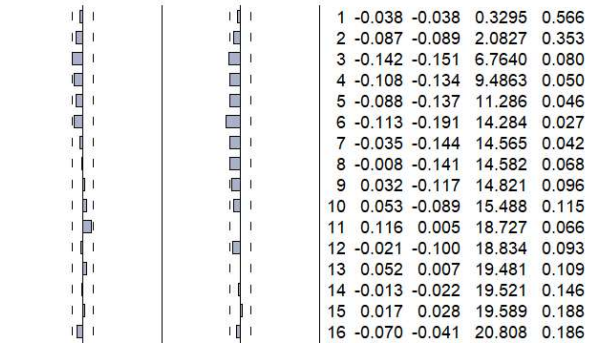
compare the absolute value of descriptive analysis results. Similar to techniques used in time analysis. We conclude the feature of continued growing and falling prices is that it is a stationary series. It has two features: **stronger autocorrelation and more discrete**. The scatter plot of the consecutive gains and losses shows that the **marginal distribution** of the gains is affected by

both the **consecutive gains and its lag effect**, indicating that there is a **certain positive correlation** between the samples of the consecutive gains and losses. At the same time, comparing the marginal distribution model also shows that the correlation between large fluctuations is relatively stronger.

Phase three - the development of research

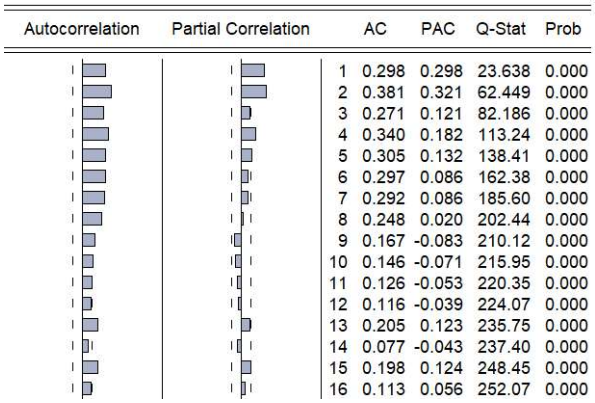
It could include proper estimation of risk measures in both high-dimensional and high-frequency data. High frequency data means that we can reduce the time to find the price fluctuation changes in ten minutes, whether there can be significant upward fluctuations in ten minutes and then how to set a new price signal to buy and sell. Based on the same analysis used before and maybe some changes in autocorrelation and new models in distributions could be found.

	Mean	Median	Std. Dev.	Skewness	Kurtosis	ADF test	Prob. *
Growing	5.454455	4.459992	3.96631	1.735776	7.027346	-19.25486	0.000
Falling	-5.416806	-4.449997	3.765479	-1.737275	7.776674	-11.98723	0.000



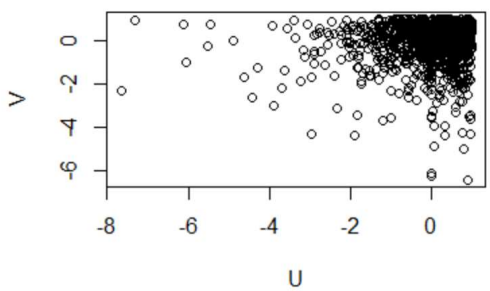
Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.038	-0.038	0.3295	0.566
		2	-0.087	-0.089	2.0827	0.353
		3	-0.142	-0.151	6.7640	0.080
		4	-0.108	-0.134	9.4863	0.050
		5	-0.088	-0.137	11.286	0.046
		6	-0.113	-0.191	14.284	0.027
		7	-0.035	-0.144	14.565	0.042
		8	-0.008	-0.141	14.582	0.068
		9	0.032	-0.117	14.821	0.096
		10	0.053	-0.089	15.488	0.115
		11	0.116	0.005	18.727	0.066
		12	-0.021	-0.100	18.834	0.093
		13	0.052	0.007	19.481	0.109
		14	-0.013	-0.022	19.521	0.146
		15	0.017	0.028	19.589	0.188
		16	-0.070	-0.041	20.808	0.186

growing



Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.298	0.298	23.638	0.000
		2	0.381	0.321	62.449	0.000
		3	0.271	0.121	82.186	0.000
		4	0.340	0.182	113.24	0.000
		5	0.305	0.132	138.41	0.000
		6	0.297	0.086	162.38	0.000
		7	0.292	0.086	185.60	0.000
		8	0.248	0.020	202.44	0.000
		9	0.167	-0.083	210.12	0.000
		10	0.146	-0.071	215.95	0.000
		11	0.126	-0.053	220.35	0.000
		12	0.116	-0.039	224.07	0.000
		13	0.205	0.123	235.75	0.000
		14	0.077	-0.043	237.40	0.000
		15	0.198	0.124	248.45	0.000
		16	0.113	0.056	252.07	0.000

Falling



Appendix:

```
library(openxlsx)
rawdata = read.xlsx("D:\\PROJECT\\Falling Knife\\10Y.xlsx")
names(rawdata)
View(rawdata)
#Standardization
xdata = scale(rawdata[,12])
ydata = scale(rawdata[,13])
install.packages('CCA')
#Classical related analysis
library(CCA)
mycca = cc(xdata,ydata)
install.packages('CCP')
#Test for significance of correlation coefficient
library(CCP)
rho = mycca$cor
n = dim(rawdata)[1]
p = dim(xdata)[2]
q = dim(ydata)[2]
p.asym(rho, n, p, q, tstat = "Wilks")
#the relationship between falling and growing price
u = mycca$scores$xscores
v = mycca$scores$yscores
plot(u[ ,1],v[ ,1], xlab = "U", ylab = "V")
```