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Behavioral Finance Anomalies

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Catalogue

1. Introduction

In this paper, we start with examining return anomalies based on information contained in historical returns in US and China stock markets respectively. We obtain empirical evidence of which the presence and magnitude of anomalies are our focus. Since existing literature has found that anomalies are time-varying, the reason of which is widely discussed by academics. Our research on recent data provide new evidence adding to the existing body of literature and contribute to the debate over causes of anomalies. If market is efficient, true anomalies are expected to decrease in magnitude since growing competition of arbitrage activities drives out profits. If there is systemic mispricing that are attributable to behavioral biases, variation of anomalies is supposed to be related to shifts in investors' behavior. Then we discuss whether existing behavioral models are compatible with anomalies found in our sample. We conduct comparative analysis between China and the US given the fact that China stock market has many unique characteristics and extremely pronounced behavioral biases. It is interesting to see how behavioral theories can be used to interpret anomalies from a highly irrational and violent market.

2. Literature review

2.1. Efficient Market Hypothesis (Fama (1970))

The definition of efficient market hypothesis is that prices fully reflect all available information. It implies that one cannot constantly earn excess returns relative to expected equilibrium returns. Fama (1970) determined three sufficient conditions for capital market efficiency: "1) there are no transaction costs in trading securities, 2) all available information is costlessly available to all market participants, and 3) all agree on the implications of current information for the current price and distributions of future prices of each security"[1]. Apparently, the assumptions are fairly strict that are not likely to be met in any markets. Nevertheless, Fama (1970) also pointed out that the assumptions are obviously sufficient but not necessary conditions for market efficiency to hold. For example, even if market participants disagree on the implication of current

[1] Malkiel, B. G., & Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. The Journal of Finance, 25(2), 383–417.

information for the price of a certain security, sophisticated investors arbitrage (assuming market is complete) on such security and push price to the equilibrium level that fully reflects all available information.

Fama (1970) test efficient market hypothesis in three forms in reference to different set of information. In the weak form, only historical information (e.g., past prices and returns), is concerned. Technical analysis fails in weak form efficient market hypothesis, while fundamental analysis is effective. Semi-strong form tests whether market prices reflect all publicly available information (e.g., earning announcement). If efficient market hypothesis in semi-strong form holds, fundamental analysis fails as well. Finally, strong form tests take into consideration not only all publicly available information, but also private information.

In mathematical language, what efficient market hypothesis says is:

$$\mathrm{E}(\mu_{it}|\mathrm{F}_{t-1}) = \mathrm{E}(R_{it} - \mathrm{E}(R_{it}|\mathrm{F}_{t-1})|\mathrm{F}_{t-1}) = 0$$

Where R_{it} is the realized return of security i at time t; μ_{it} is the excess return of security i at time t; F_{t-1} is the information set assumed to be fully reflected in the price at time t-1; $\mathrm{E}(R_{it}|\mathrm{F}_{t-1})$ is the expectation of R_{it} conditioning on the information set F_{t-1}.

2.2. Anomalies

An extensive body of literature has documented evidence of predictability of stock return patterns. Many researchers looked to exploit these return patterns based on a wide variety of anomaly variables and reported statistically significant abnormal returns that are not explained by Capital Asset Pricing Model (CAPM) of Sharpe (1964) and Lintner (1965), or presented cross-section of average stock returns.

These findings posit doubts on efficient market hypothesis (Fama (1970)), of which the implication is that trading on a set of information cannot generate unexpected returns, thus no one can ever beat the market. Though anomaly variable strategies seemingly invalidate efficient market hypothesis even in its weak form in an explicit way, the causes of such abnormal profits are indeed controversial and extensively debated in academics. One school attributes the success of anomaly strategies to systemic mispricing that arises from behavioral biases of irrational investors. The assumptions of efficient market hypothesis are clearly violated. Another school focus on whether asset pricing model is accurately specified, particularly whether related risks are effectively and thoroughly accounted for, arguing that varying risk factors, once properly captured, explain in a large part documented abnormal returns. Alternative explanations concern data mining issue or claim that such return patterns are simply results of chances, that occur over a long horizon.

The most classic anomalous return patterns are size factor and value factor. Banz (1981) finds that stocks with low capitalization have unusually high average returns, put differently small firms outperform large firms. Rosenberg, Reid, and Lanstein (1985), Chan, Hamao, and Lakonishok (1991), Fama and French (1992) ducument evidence suggesting that stocks with high book-to-market ratio earn abnormally high returns, put differently, value stocks outperform growth stocks. Fama-French (1992) put forward a three-factor model that expands on the capital asset pricing model (CAPM) by adding size risk and value risk factors to the market risk factor in CAPM. This model powerfully characterizes the cross section of average US stock returns over the 1993-1990 period despite the economic rationale behind size and value effects were not clearly identified. Since the birth of three-factor model, it has become a widely used asset pricing model among academics and practitioners when required returns are needed.

However, Fama-French model fails to account for a range of anomalies in vast literature, among which momentum effect is prominent in recent years. Jegadeesh and Titman(1993) show that stock returns over the last year have a tendency to continue for the next few months. Buying past winners and selling past losers generate substantial abnormal returns. Carhart(1997) proposes a four-factor model that includes a momentum factor to extend Fama-French three-factor model. Haugen and Baker (1996) and Cohen, Gompers, and Vuolteenaho (2002) uncover profitability anomaly wherein more profitable firms have higher average stock returns, while Fairfield, Whisenant, and Yohn (2003) and Titman, Wei, and Xie (2004) show that heavy firm investments signal lower stock returns. Sloan (1996) investigates the accruals anomaly showing that stocks with greater non-cash components of earnings earn lower returns. Daniel and Titman (2006) and Pontiff and Woodgate (2008) show that there is a negative relation between net stock issues and average returns.

2.3. Momentum

Momentum strategies offer investors high Sharpe ratio, higher than the market, value and size factors (Barroso and Santa-Clara (2015)), which makes the profitability of momentum strategies particularly interesting. Jegadeesh and Titman (1993) document that past six-month winner stocks (in the top decile) outperform past six-month loser stocks (in the bottom decile) by as much as 1.3% per month in US market over the period from 1965 to 1989. The authors extend this strategy to the 1990s (Jegadeesh and Titman (2001)) and show that profits to momentum strategies remain significant, which makes data mining a less convincing explanation. Notably, momentum strategies are not only persistent but also robust to many other markets. Rouwenhorst (1998) obtain similarly significant profits in 12 European countries over the time period from 1978 to 1995. Korajczyk and Sadka (2004) take into consideration market frictions induced by trading and prove momentum profits remain significant.

There has been an extensive literature to explore the source of momentum profitability given its intriguing persistence and robustness. Behavioral theories are proposed indicating that irrational agents have cognitive biases, as a result drive systematic mispricing. Daniel, Hirshleifer, and Subrahmanyam (1998) assume investors typically exhibit overconfidence bias, where they overestimate their forecast accuracy and underestimate the range of forecast errors. In DHS model, specifically, investors are over-confident about private information, hence tend to put more weight on private information relative to public information. Another bias assumed in DHS model is self-attribution where people take credit for success and blame external circumstances for failure to the extent more than they should. When public information come that conform to their prior beliefs, their confidence is overly boosted. However, non-conforming public information do not reduce as much their confidence due to self-attribution bias. The asymmetric impacts of public information in effect lead to confirmation on private information and overreaction. As a result, prices are pushed to deviate from its fundamental value, a typical momentum process. When public information eventually reaches a high level, overreaction is corrected. Stock prices gradually revert to its fundamental value, which explains long-term reversal documented by DeBondt and Thaler (1985).

Hong and Stein (1999) propose a behavioral model based on initial underreaction and subsequent overreaction. HS emphasize on heterogeneities across investors. “News-watchers" exclusively trade on information, whereas "momentum-traders" exclusively trade on changes in past prices. Key assumptions in this model are: 1) firm-specific information diffuse gradually; 2) investors cannot make unbiased expectation from information contained in past prices. Initially, when new information arrives, news-watchers are the first to react. However, because of the slow diffusion of news, it takes time for new information to be fully reflected in prices, hence under-reaction. As prices start to exhibit observable movements, momentum-traders are attracted to catch the trend. Their trading activities lead to subsequent overreaction.

In Barberis, Shleifer, and Vishny (1998), investors exhibit 1) conservatism bias where they believe in a mean-reverting return pattern, tend to stick to prior beliefs, and are and slow to update their expectation when new information come; 2) representativeness bias where they believe in a trending return pattern and extrapolate short-term trend. The BSV model assume stock returns follow random walk that investors are unable to recognize. Instead, investors update their expectations using Bayesian rule with regard to either mean-reverting or trending return patterns, depending on market states.

Following previous research, Hong, Lim, and Stein (2000) investigate the effects of size and analyst coverage on the magnitude of profits to momentum strategies and obtain results consistent with the hypothesis that firm-specific information diffuses only gradually. Lee and Swaminathan (2000) show that past trading volume forecasts both the magnitude and persistence of price momentum, suggesting that trading volume can proxy for interest and speed at which information diffuses into prices.

Another strand of literature claims that profits of these strategies are compensation for risks. Conrad and Kaul (1998) and Berk, Green, and Naik (1999) argue that profits of momentum strategies are results of cross-sectional variation in expected returns rather than time-series return patterns. Jegadeesh and Titman (2001) argue that reversals in the post-holding period reject the claim of Conrad and Kaul that momentum profits are due to variations in expected returns. There are evidence pointing out that the magnitude of momentum profitability and reversals are related to business cycle and macroeconomics variables (Chordia and Shivakumar(2002)), suggesting common factors could play a role as an explanation for momentum payoffs. Fama (1998) argue that anomalies like momentum effect arise because improper asset pricing models are employed. He also claims that over- and under-reaction co-exist in market thus can't be determined in advance, hence anomalies are random events.

One can reasonably expect that anomalies should diminish as increasing arbitrage activities drive down such anomalous returns. Assuming such anomaly is indeed generated by agents' irrationality in information processing, momentum profits should be largely driven by firm-specific features. Hence, one can effectively extract momentum profits by holding a diversified arbitrage portfolio which is constructed to have low systematic risk. The fact that momentum anomaly remains persistent long after its dissemination to public indicates that behavioral models may not provide a full picture.

2.4. Reversals

According to overreaction hypothesis (Kahneman and Tversky (1982)), people have a tendency to overweight new information and underweight prior information, thus fail to apply Bayer's rule of conditional probability when updating their beliefs. DeBondt and Thaler (1985) first apply the hypothesis in finance, arguing that initial overreaction and subsequent correction predict past loser stocks to earn an abnormally higher return than past winner stocks and vice versa. As the authors suggest, an arbitrage portfolio of buying past losers and selling past winners can generate abnormal profits on a risk-adjusted basis. The strategy is also named contrarian strategy.

Reversals are discussed from both short-term and long-term perspective. Momentum and long-term reversal generally occur as subsequent events as they are highly related in terms of causes. Long-term reversals usually take 3-5 years. Short-term reversals typically take a few days or weeks. Jegadeesh (1990) reported that a contrarian strategy based on previous monthly returns obtained significant excess profits over 1934-1987 periods. Zarowin (1990), Lo and MacKinlay (1990) also find abnormal return to short-run contrarian strategy. Although there is plenty of empirical evidence supporting the profitability of short-term contrarian strategies, there is also disagreement on whether such profits are truly results of overreaction. Alternative explanations include size effects (Zarowin (1990), Chopra, Lakonishok, and Ritter (1992)), bid-ask bounce (Conrad and Kaul, (1993)), lead-lag structures (Lo and MacKinlay (1990)), seasonality effect (Zarowin (1990) and time-varying market risk (Ball and Kothari (1989)). Akhigbe, Gosnell, and Harikumar (1998) report that after taking into consideration bid-ask spread, it is impossible to exploit the excess return net of transaction costs.

2.5. China stock market

Although the predictability of stock returns based on past prices has been extensively investigated, there is not as many researches in China. The lack of investigations in China is partly due to the relatively short history of stock trading and limited amount of data. As integration of global capital markets increases, there are less constraints on foreign capital flowing across border. China market has attracted increasing interests from global investors. Investigations on well-known return patterns in the context of China stock market not only add to the existing body of literature with emerging market evidence, but also create value for global investors.

China stock market is distinct from others in many aspects. There are two stock exchanges in mainland China, based in Shanghai and Shenzhen, both established in 1990. The history of exchange trading is less than 30 years wherein the period of first 10 years from 1990 to 2000 is a transition period and experienced great volatility. Moreover, public data are not of high quality because incomplete regulatory framework and lenient supervision give chance to data manipulation.

The most prominent characteristics of China stock market maybe the extent of influence of government regulations and composition of investors. Whereas stock markets in developed countries are primarily driven by market information, in China, government regulations can exert huge impacts on stock market and send strong signals to shape investors' behavior. Unlike US equity market that is dominated by institutional investors, china equity market has a much larger portion of individual investors, who are unsophisticated and somewhat irrational. They trade like noise by speculating based on narrow set of information, mainly historical trends, rumors and also investors' sentiment. Unsophisticated individual investors tend to demonstrate herding instinct where they follow the decision of other investors rather than making independent decisions. Herding behavior has great implications in financial market. For instance, financial bubbles can be somewhat attributed to herding behavior, when investors make the same or similar investments out of the fear that they may miss out profitable opportunities. Such exuberant behavior drives a rapid market rally beyond its intrinsic value without fundamental justification. Chinese investors also tend to hold stocks for a shorter time horizon than do American investors, consistent with their speculative investment style. The high average turnover ratio causes excess volatility. As rumors and sentiment are the primary driving forces of China market, it is not a are phenomenon that speculators try to manipulate stock prices though disseminating rumors or generating fake sentiment. Such practice is particularly featured by small caps because observable trends can be readily started in small caps with fewer funds.

China stock market is terribly volatile. To tackle the volatility issue, Chinese government has established stabilizing mechanism aimed at slowing down selloffs out of panic or oversensitivity that are disastrous. Yet, such mechanism often does not end up with desired results. One example is the failed experiment with circuit breakers. On Jan 4 2016, to avoid large plunges as the market experienced in 2015, the Chinese government implemented new circuit breakers, which stated that if the benchmark CSI 300 index (made up of 300 A-share stocks listed on the Shanghai or Shenzhen Stock Exchange) falls by 5% in a day, trading would be halted for 15 minutes. If CSI 300 drops by 7% drop, trading would be halted for the rest of the day. On the very day and the day after the introduction, the market fell by 7% and the circuit breaker was triggered. As the circuit breaker turned out to be counterproductive with regard to improving stability, the Chinese government suspended the circuit breakers only 4 days after they had been put into effect. As seen in light of the event, China stock market is extremely regulation-driven and inclined to overreact.

3. Methodology

3.1. Data source and Pre-processing

We sourced the US market and securities trading data from CRSP. They range from Jan 3, 2007 to Dec 31, 2018. The daily return is provided by the database. It is calculated as follows.[2]

For time t (a holding period), let:

t? = time of last available price < t

r(t) = return on purchase at t?, sale at t

p(t) = last sale price or closing bid/ask average at time t

[2] https://wrds-web.wharton.upenn.edu/wrds/query_forms/variable_documentation.cfm?vendorCode=CRSP&libraryCode=crspa&fileCode=dsf&id=ret

d(t) = cash adjustment for t

f(t) = price adjustment factor for t

p(t') = last sale price or closing bid/ask average at time of last available price < t.

then r(t) = [(p(t)f(t)+d(t))/p(t')]-1

Based on it we created a few variables, dxd, to represent the accumulative return over the last x trading days. They are calculated as below.

$$\mathrm{d1d_i} = \mathrm{r_{i-1}}$$

$$\mathrm{d3\,d_i} = \prod_{j=i-3}^{i-1}(r_j+1)-1$$

$$\mathrm{d21\,d_i} = \prod_{j=i-21}^{i-1}(r_j+1)-1$$

$$\mathrm{d63\,d_i} = \prod_{j=i-63}^{i-1}(r_j+1)-1$$

$$\mathrm{d252\,d_i} = \prod_{j=i-252}^{i-1}(r_j+1)-1$$

The data of CSI 300 is sourced from Yahoo Finance. It ranges from Jan 31, 2007 to Mar 1, 2017. We took the daily Adjusted Close Price as the standard, based on which we created the following variables.

$$Return_i = \frac{S_i}{S_{i-1}} - 1$$

$$d1d_i = \frac{S_{i-1}}{S_{i-2}} - 1$$

$$d3d_i = \frac{S_{i-1}}{S_{i-4}} - 1$$

$$d21d_i = \frac{S_{i-1}}{S_{i-22}} - 1$$

$$d63d_i = \frac{S_{i-1}}{S_{i-64}} - 1$$

$$d252d_i = \frac{S_{i-1}}{S_{i-253}} - 1$$

3.2. Methods

We used time series regression to study the momentum effects in the S&P 500 index and the CSI 300 index.

We applied panel analysis to study the momentum effects in the US stocks and make comparison among them.

Based on the regression results, trading strategies were designed, and simulations were run to testify them.

4. Analyses

4.1. Analysis on US Market

Based on the regression of S&P 500 daily return on its first-order difference, last trailing month's (last 21 trading days') return, and last trailing year's (last 252 trading days') return, we discovered a significant negative correlation between S&P 500 daily return and its first-order difference.

```
Call:
lm(formula = sprtrn ~ d1d + d21d + d252d, data = mkt)

Residuals:
      Min        1Q    Median        3Q       Max 
-0.092514 -0.004278  0.000544  0.005278  0.112587 

Coefficients:
              Estimate Std. Error t value Pr(>|t|)    
(Intercept)  0.0003245  0.0002616   1.240    0.215    
d1d         -0.0903422  0.0193094  -4.679 3.03e-06 ***
d21d        -0.0071748  0.0053124  -1.351    0.177    
d252d        0.0002634  0.0014474   0.182    0.856    
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.01263 on 2764 degrees of freedom
  (252 observations deleted due to missingness)
Multiple R-squared:  0.009789, Adjusted R-squared:  0.008715 
F-statistic: 9.108 on 3 and 2764 DF,  p-value: 5.356e-06
```

The negative correlation between S&P 500 daily return and its first-order difference is obvious, compared with the intercept and other factors.

```
Call:
lm(formula = (sprtrn > 0) ~ (d1d > 0), data = mkt)


Residuals:
    Min      1Q  Median      3Q     Max 
-0.5687 -0.5164  0.4313  0.4836  0.4836 


Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept)  0.56874    0.01395  40.759  < 2e-16 ***
d1d > 0TRUE -0.05235    0.01899  -2.757  0.00587 ** 
---
```

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.4979 on 2766 degrees of freedom

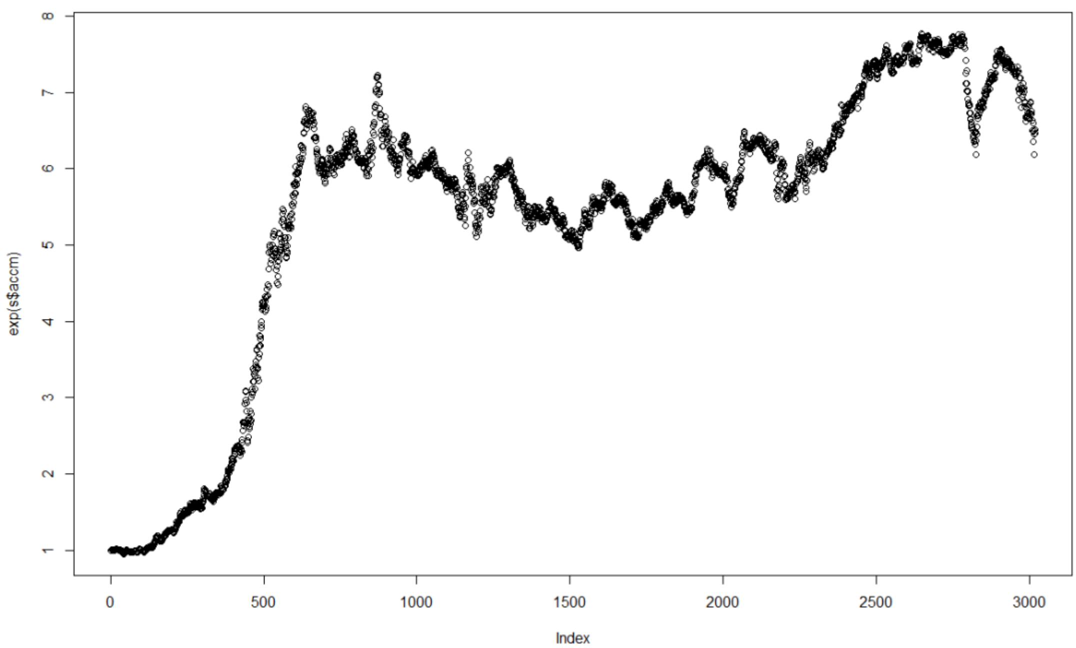
(252 observations deleted due to missingness)

Multiple R-squared: 0.002741,   Adjusted R-squared: 0.00238

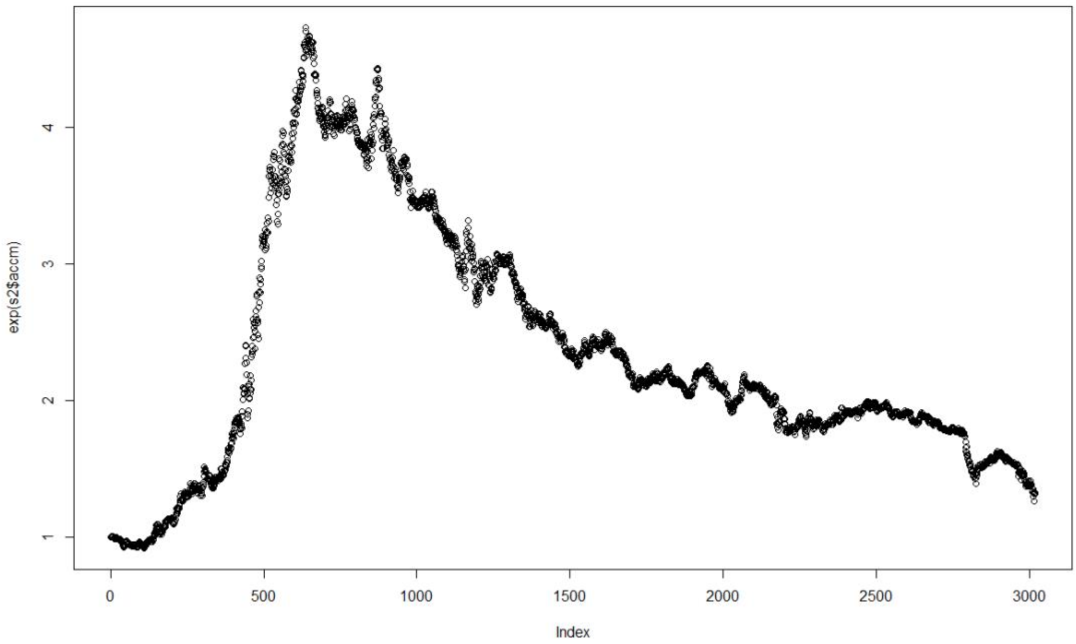
F-statistic: 7.601 on 1 and 2766 DF, p-value: 0.005871

Based on the finding above, we could implement a straightforward trading strategy.

1. To be long the index when the daily return is negative, and to close the position the next trading day.
2. To be short the index when the daily return is positive, and to close the position the next trading day.



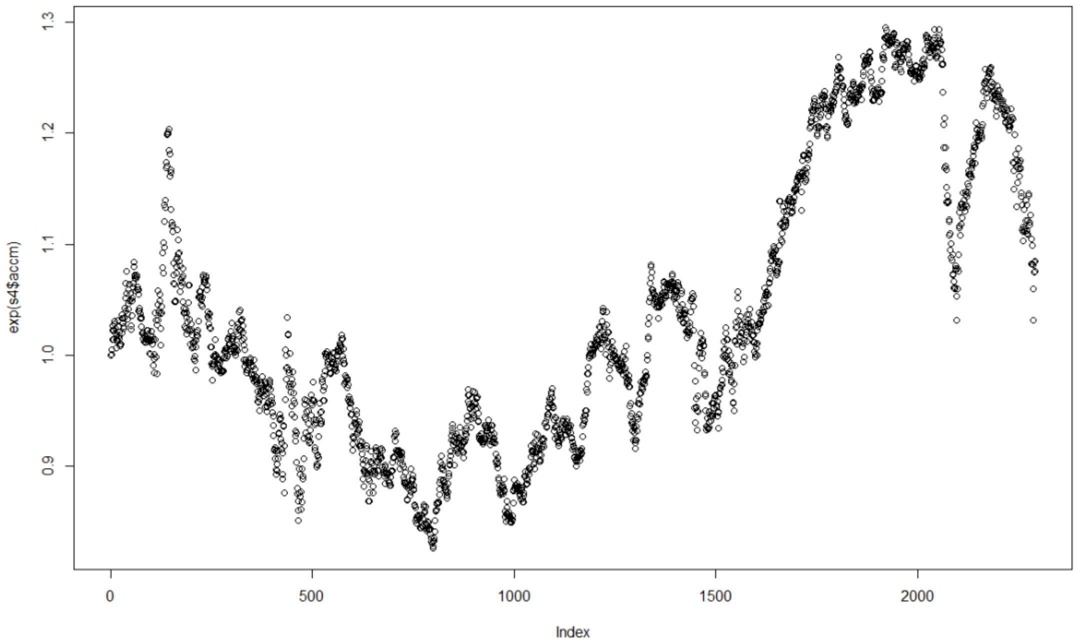
Generally, this trading strategy generates an excellent yield. Over 10 years, the investment realised an increase of more than 500%, i.e. an annualised return of 20.6%, and reached nearly 700% at its peak.

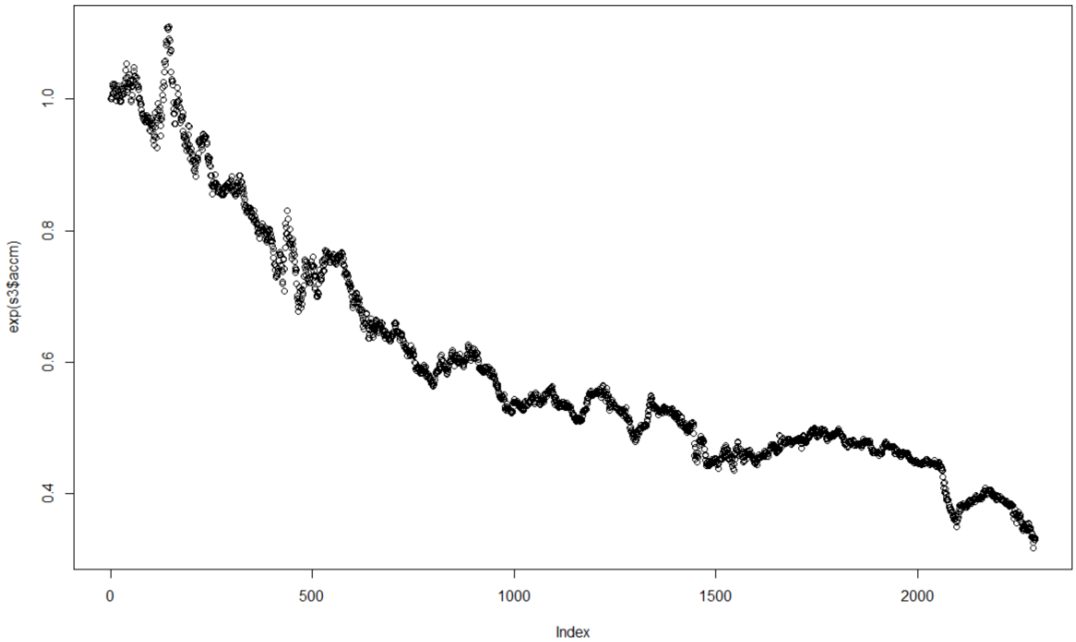


However, with a 0.05% trading cost applied, the performance was completely turned around. The investment value ended up with 1.329, compared to 2.237, the index itself.

It is noticeable on the graph that the portfolio value split into 2 periods, before- and after-2009. It was monotonically increasing between 2007 and 2009, when the financial crisis was taking place, and decreasing the rest of time.

To confirm the speciality, we removed the period from 2007 to 2009. As is expected, this trading strategy does not profit as before. Below are the performances of it with and without trading costs.





When 2008 is removed from the regression, the significance of the first-order difference is drastically decreased.

```
Call:

lm(formula = sprtrn ~ d1d, data = tail(mkt, -730))
```

```
Residuals:
      Min        1Q    Median        3Q       Max
-0.067080 -0.003799  0.000180  0.004621  0.047944

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.0004202  0.0001970   2.133   0.0331 *
d1d         -0.0453718  0.0208789  -2.173   0.0299 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.009419 on 2288 degrees of freedom
Multiple R-squared:  0.00206,	Adjusted R-squared:  0.001624
F-statistic: 4.722 on 1 and 2288 DF,  p-value: 0.02988
```

4.2. China A Share Market

We replicated the same analysis to CSI 300 Index, which is a capitalization-weighted stock market index designed to replicate the performance of top 300 stocks traded in the Shanghai and Shenzhen stock exchanges.

We ran a regression of return on the historical returns.

```
Call:
lm(formula = Return ~ d1d + d3d + d21d + d63d + d252d, data = csi)


Residuals:
      Min        1Q    Median        3Q       Max
-0.084679 -0.008022  0.000349  0.008625  0.094578

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept)  7.018e-05  3.917e-04   0.179   0.8578
d1d          6.916e-02  3.056e-02   2.263   0.0237 *
```

```
d3d        -4.607e-02  2.193e-02  -2.101   0.0358 *
d21d        5.872e-03  5.942e-03   0.988   0.3232
d63d        4.411e-03  3.092e-03   1.427   0.1538
d252d      -1.983e-03  1.069e-03  -1.856   0.0636 .
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.01826 on 2189 degrees of freedom
  (252 observations deleted due to missingness)
Multiple R-squared:  0.006184,     Adjusted R-squared:  0.003914
F-statistic: 2.724 on 5 and 2189 DF,  p-value: 0.01844
```

We took the backward approach to select variables, and ended up as below.

```
Call:
lm(formula = Return ~ 0 + d1d + d3d + d63d + d252d, data = csi)

Residuals:
     Min        1Q    Median        3Q       Max
-0.084531 -0.007902  0.000414  0.008706  0.094390

Coefficients:
       Estimate Std. Error t value Pr(>|t|)
d1d    0.069007   0.030555   2.258   0.0240 *
d3d   -0.041805   0.021493  -1.945   0.0519 .
d63d   0.006213   0.002492   2.493   0.0127 *
d252d -0.002035   0.001061  -1.919   0.0551 .
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.01825 on 2191 degrees of freedom
  (252 observations deleted due to missingness)
```

```
Multiple R-squared:  0.005727,	Adjusted R-squared:  0.003912
F-statistic: 3.155 on 4 and 2191 DF,  p-value: 0.01346
```

This result accord to the conclusion of past researches, that the return, in short term (3 days in our model), tends to revert from the trend of the previous trading days, in midterm (63 days in our model, i.e. 3 months) keeps the trend, and in long term (252 days in our model, i.e. 1 year) reverts. That is to say, short-term reversal, mid-term momentum, and long-term reversal in the CSI 300 index are all confirmed by this model.

3.2.1. Multicollinearity and Modification

However, the model turned out problematic when we continued removing variables. As we removed either d1d or d3d, the other became immediately insignificant. Besides, d252d turned insignificant as well when d63d was abandoned. This finding warns of the multicollinearity problem.

To avoid the problem, we introduced 2 new variables, dd2 and dd190. Dd2 denotes the return of last 3 but 1 trading days. It is computed by

$$\mathrm{dd2} = \frac{index_{i-1}}{index_{i-3}} - 1$$

Dd190 denotes the return of last 252 but 63 trading days. It is computed by

$$\mathrm{dd190} = \frac{index_{i-63}}{index_{i-252}} - 1$$

In this way, we mitigated the effect of the collinearities between d1d and d3d, and between d63d and d252d.

```
Call:
lm(formula = Return ~ d1d + dd2 + d21d + d63d + dd190, data = csi)


Residuals:
      Min        1Q    Median        3Q       Max
-0.084276 -0.008012  0.000356  0.008630  0.094874


Coefficients:
            Estimate Std. Error t value Pr(>|t|)
```

```
(Intercept)  7.949e-05  3.928e-04   0.202   0.8396
d1d          2.323e-02  2.194e-02   1.059   0.2898
dd2         -4.624e-02  2.198e-02  -2.103   0.0355 *
d21d         5.969e-03  5.942e-03   1.005   0.3152
d63d         2.274e-03  2.946e-03   0.772   0.4402
dd190       -1.796e-03  1.049e-03  -1.712   0.0871 .
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.01826 on 2189 degrees of freedom
  (252 observations deleted due to missingness)
Multiple R-squared:  0.005953,     Adjusted R-squared:  0.003683
F-statistic: 2.622 on 5 and 2189 DF,  p-value: 0.02264
```

After reducing variables through the backward approach, the model ended up as below.

```
Call:
lm(formula = Return ~ 0 + dd2 + d21d + dd190, data = csi)

Residuals:
     Min        1Q    Median        3Q       Max
-0.085388 -0.007897  0.000399  0.008814  0.095726

Coefficients:
       Estimate Std. Error t value Pr(>|t|)
dd2   -0.046941   0.021966  -2.137   0.0327 *
d21d   0.009894   0.004642   2.132   0.0332 *
dd190 -0.001833   0.001039  -1.765   0.0777 .
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.01826 on 2192 degrees of freedom
```

```
(252 observations deleted due to missingness)
Multiple R-squared:  0.005153,     Adjusted R-squared:  0.003792
F-statistic: 3.785 on 3 and 2192 DF,  p-value: 0.01008
```

The result remains the same as before. The short-term reversal, the mid-term momentum, and the long-term reversal are all significant. Noticeably, d21d replaces d63d, which means last 1 month's return instead of last 3 months' is a better predictor.

What is interesting is that dd2 and dd190, without d1d and d63d, are significant. Although not as straightforward as d3d and d252d, dd2 and dd190 are statistically more significant and economically representative enough of the short-term and the long-term returns.

3.2.2. Curse

A rumour called Thursday Curse is widely believed in China. As it is named, Thursday Curse is a phenomenon that the Chinese stock markets witness negative anomalies on Thursdays. To examine the rumour, we brought a logical variable (wd == "Thursday"), denoting whether the trading day is Thursday, to the model above.

```
Call:
lm(formula = Return ~ dd2 + d21d + dd190 + (wd == "Thursday"),
    data = csi)


Residuals:
      Min        1Q    Median        3Q       Max
-0.085840 -0.007954  0.000210  0.008661  0.097125


Coefficients:
                    Estimate Std. Error t value Pr(>|t|)
(Intercept)          0.0004515  0.0004382   1.030   0.3029
dd2                 -0.0482761  0.0219701  -2.197   0.0281 *
d21d                 0.0098961  0.0046413   2.132   0.0331 *
dd190               -0.0018683  0.0010459  -1.786   0.0742 .
wd == "Thursday"TRUE -0.0018138  0.0009743  -1.862   0.0628 .
```

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.01825 on 2190 degrees of freedom

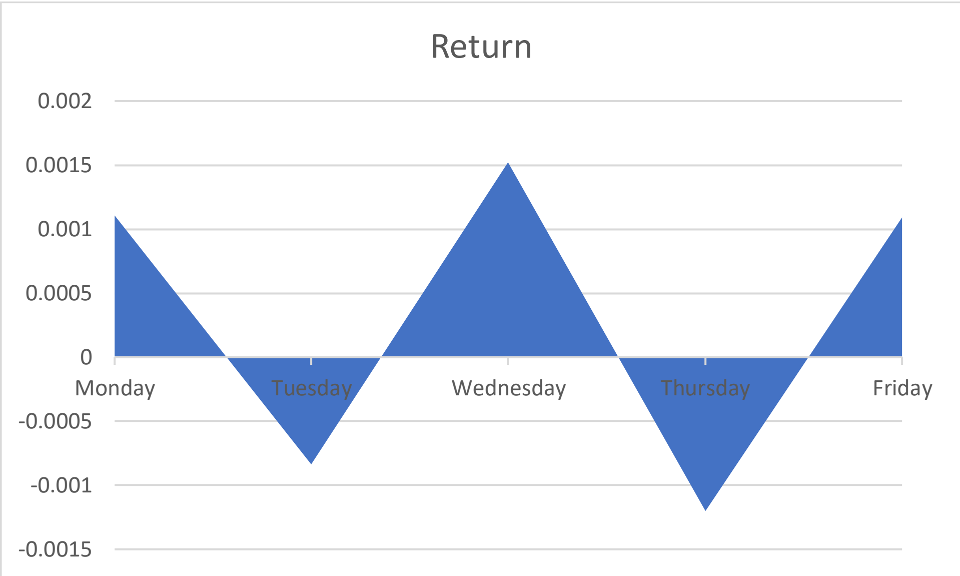
(252 observations deleted due to missingness)

Multiple R-squared: 0.006748,   Adjusted R-squared: 0.004934

F-statistic: 3.72 on 4 and 2190 DF, p-value: 0.005057

The result demonstrates that Thursday is a significant negative factor on the daily market return.

The graph below shows the effect of each workday on the daily market return.



Previous studies have some explanations.

1. Delivery system

Unlike the “T+0” delivery systems in the US, China’s A Share Market adopts the “T+1” system, where the trades are delivered the next day after the deals. As a result, investors, in order to ensure liquidity over the weekend, have to sell the shares on Thursday.

2. Risk averse

Friday evenings and weekends are a time when the Chinese government and companies tend to announce policies and disclose information. Investors prefer not to hold positions over the weekend to avoid risks.

On top of that, historical anomalies have raised investors’ risk aversion on Thursday.

3.2.3. Consecutive Movement

Another rumour in China is that the market movement and the investors sentiment turns around every 3 days.

We introduced a variable to test it. L3d equals to 1 when the last consecutive trading days' returns are all positive, to -1 when they are negative, and to 0 otherwise.

$$\mathrm{l3d} = \begin{cases} 1 & r_{i-1}, r_{i-2}, r_{i-3} > 0 \\ -1 & r_{i-1}, r_{i-2}, r_{i-3} < 0 \\ 0 & \text{otherwise} \end{cases}$$

We ran a regression.

```
Call:
lm(formula = Return ~ l3d, data = csi)


Residuals:
     Min        1Q    Median        3Q       Max
-0.092562 -0.008333  0.000539  0.009552  0.092855


Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.0003625  0.0003851   0.941    0.347
l3d         -0.0002008  0.0007513  -0.267    0.789


Residual standard error: 0.01894 on 2441 degrees of freedom
  (4 observations deleted due to missingness)
Multiple R-squared:  2.927e-05,    Adjusted R-squared:  -0.0003804
F-statistic: 0.07145 on 1 and 2441 DF,  p-value: 0.7893
```

The t value of l3d is -0.267, far from significant.

3.2.4. Forecast and Trading Strategy

On the basis of our model, we developed an investment strategy on the index.

Method

We divided the observations into 2 subsets, the first 2000 as the training set and the last 447 as the test set.

We ran the model Return ~ dd2 + d21d + dd190 + (wd == "Thursday") with the training set and got the regression coefficients. We then applied the model to the test set to forecast the returns.

We computed the quantiles of the fitted values of the training sets, a took the 25% and 75% quantiles as the short and the long thresholds.

For each period, we would be long the index when the forecasted return was greater than the long threshold, and clear the position the next trading day.

We would be short the index when the forecasted return was less than the short threshold, and clear the position the next trading day.

We would hold no position otherwise.

We imposed a 0.000345 trading cost.

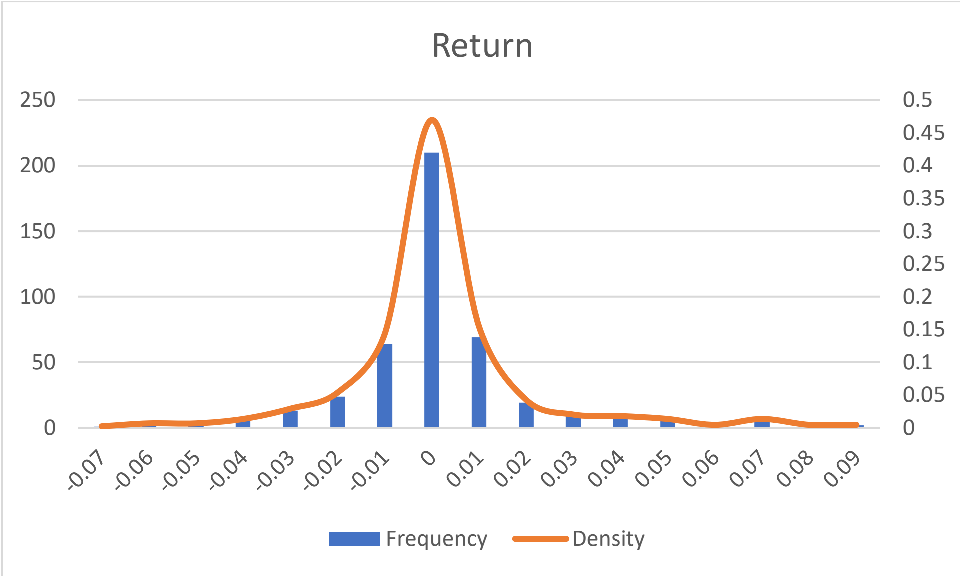
Result

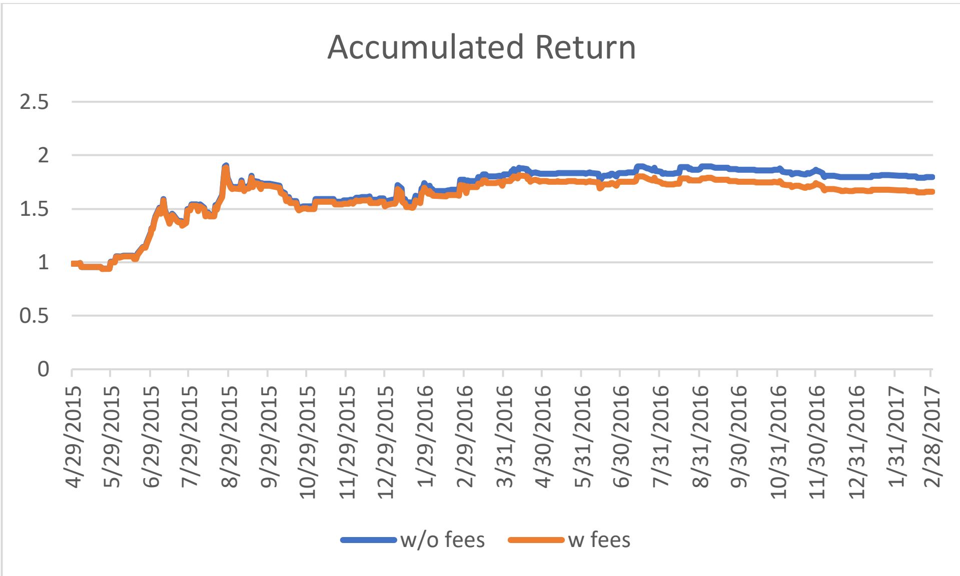
We got a summary of the daily returns drawn by the strategy.

Min.	1^{st} Qu.	Median	3^{rd} Qu.	Max.
-0.06404	-0.00026	0	0.001286	0.087479

Mean	Std.	Skew.	Kurt.
0.001462	0.017211	1.355318	7.301673

As it shows, the strategy led to a positive average daily return, and a positive skewness. Below is the distribution of the returns.



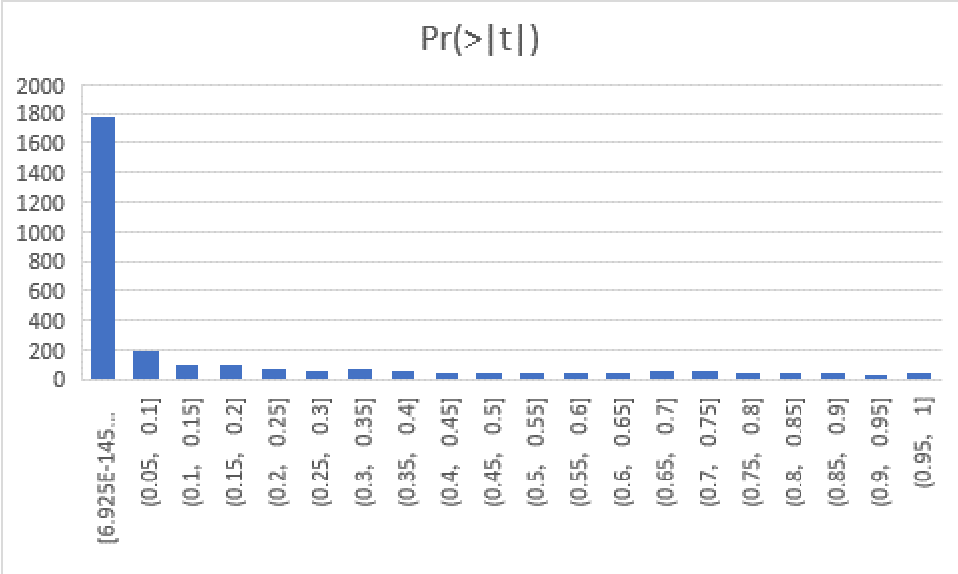


Overall, the strategy realized returns of 79.82% without trading costs and 66.61% with trading costs, which are respectively 39.31% and 33.21% after annualization.

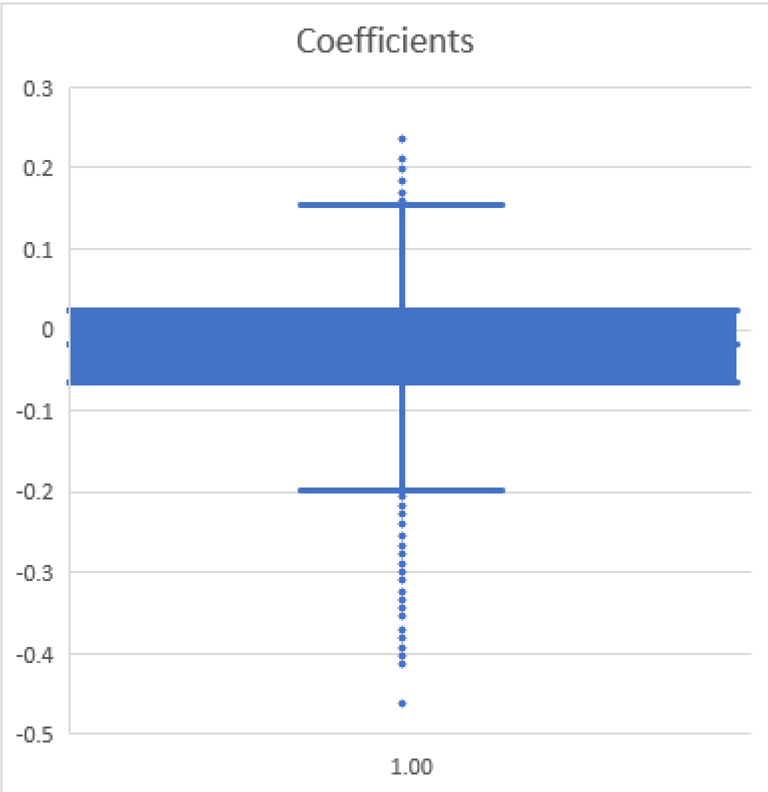
4.3. US Stocks Momentum and Trading Strategies

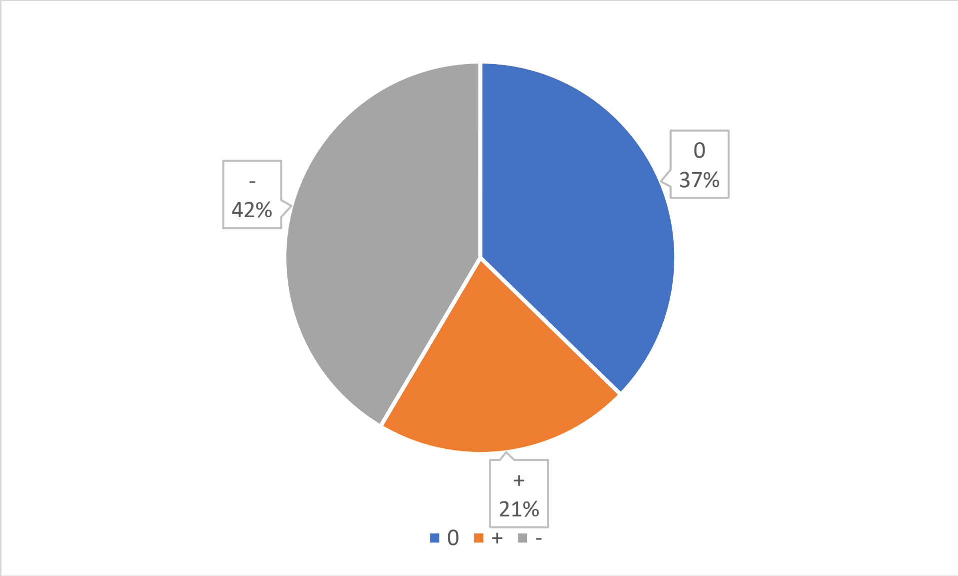
We ran a regression to each stock to study their momentum effects.

Of the majority of the stocks, the daily returns are significantly correlated to the previous day's returns, which explains the short-term reversal in the market returns.



The coefficients are generally negative, with mean of -0.03085 and a long tail on the left side.





s

42% of the stocks have significant negative coefficient, 21% positive, and the other 37% are not significant enough.

5. Conclusion

In this research, we studied the momentum and reversal effect in the US and the China stock market.

In the S&P 500 index, the short-term reversal is remarkable while the mid-term momentum and long-term reversal are not. The trading strategy on the basis of one-day reversal is profitable between 2007 and 2009, and no longer works after 2009.

Most of the US stocks show a significant short-term momentum or reversal effect, among which reversals are more commonly observed.

In China, the short-term reversal, the mid-term momentum, and the long-term reversal are all obvious in the CSI 300 index. On top of these factors, Thursday is confirmed to have a negative impact on the market daily return. Our forecasting model works well in predicting the rise and fall of the market, and the trading strategy realized over 30% annualized return in simulations.

We think it is a topic worth further researches the difference between the short-term reversals of the period 2007-2009 and that after 2009.

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7. Appendix

7.1. US Market Trading

This script is used in computing the returns with the trading strategy in the Chapter US Market.

```
sp <- function(t = 1, fee = 0) {
  yield <- 0
  output <- data.frame(return = 0, accm = 0)
  pos <- 0
  for (i in t:(length(mkt$sprtrn)-1)) {
    pos.old <- pos

    if (mkt$sprtrn[i] > 0) {
      pos <- -1
    } else if (mkt$sprtrn[i] < 0) {
      pos <- 1
    } else {
      pos <- 0
    }
    if (pos * pos.old == 0 ) {
      cost <- fee
    } else if (pos != pos.old) {
      cost <- 2*fee
    } else cost <- 0
    rtn <- mkt$sprtrn[i+1] * pos - cost
    yield <- yield + rtn
    output <- rbind(output, c(rtn, yield))
```

```
  }
  return(output)
```

7.2. China A Share Market Trading

This script is used in computing the returns with the trading strategy in the Chapter China A Share Market.

```
hushen <- function(data, t = 2000, fee = 0) {
  data.lm <- lm(Return ~ dd2 + d21d + dd190 + (wd == "Thursday"), data[1:t,])
  len <- length(data[,1]) - t
  thresholds <- quantile(data.lm$fitted.values)
  forecast <- as.matrix(tail(data, len)[, c("dd2", "d21d", "dd190", "Thurs")]) %*%
    data.lm$coefficients[2:5] + data.lm$coefficients[1]
  test <- data.frame(tail(data$Return, len), forecast)

  yield <- 1
  output <- data.frame(return = 0, accm = 0)
  pos <- 0
  for (i in 1:(len-1)) {
    pos.old <- pos

    if (test[i,2] > thresholds[4]) {
      pos <- 1
    } else if (test[i,2] < thresholds[2]) {
      pos <- -1
    } else {
      pos <- 0
    }
```

```
    if (pos != pos.old) {
      if (pos * pos.old == 0 ) {
        cost <- fee
      } else cost <- 2*fee
    } else cost <- 0
    rtn <- test[i,1] * pos - cost
    yield <- yield * (1+rtn)
    output <- rbind(output, c(rtn, yield))
  }
  return(output)
}
```

7.3. Stock Data Pre-processing

```
aa.d <- aa[,c(1,2,9)]
aa.d <- cbind(aa.d, d1d = NA, d21d = NA, d252d = NA)
index <- 253:3020
t <- index
while (tail(index,1) < 8489220) {
  t <- t+3020
  index <- c(index, t)
}
aa.d$d1d[index] <- aa.d$RET[index-1]

for (i in seq(253, 8489220, 3020)) {
  aa.d[i,5] <- prod(aa.d[(i-21):(i-1),3]+1)-1
  aa.d[i,6] <- prod(aa.d[(i-252):(i-1),3]+1)-1
  for (j in (i+1):(i+2767)) {
```

```
    aa.d[j,5] <- (aa.d[j-1,5]+1) / (aa.d[j-22,3]+1) * (aa.d[j-1,3]+1) - 1
    aa.d[j,6] <- (aa.d[j-1,6]+1) / (aa.d[j-253,3]+1) * (aa.d[j-1,3]+1) - 1
  }
}
stock.reg <- list()
for (i in 1:2811) {
  gupiao <- aa.d[((i-1)*3020+253):(i*3020),]
  result <- summary(lm(RET ~ d1d + d21d + d252d, gupiao))
  stock.reg[[i]] <- list(stock = stock[i], reg = result)
}
# for (i in index) {
#   if () {
#
#   }
#     aa.d[i,5]   <-   c(aa.d[i-1,3],   prod(aa.d[(i-22):(i-1),3]+1)-1,prod(aa.d[(i-253):(i-1),3]+1)-1)
# }

for (i in seq(3020, 8489220, 3020)) {
  gupiao <- aa.d[(i-3020+253):i,]
  summary(lm(RET ~ d1d + d21d + d252d, gupiao))
}
```

7.4. Stock Trading

```
tragic <- function(){
  principle <- 1
  junzhi <- 0
```

```
  jieguo1 <- NULL
  jieguo2 <- NULL
  for (i in 1:3019) {
    portfolio <- (chrono[[i]]$RET >0.05)
    ret <- na.omit(chrono[[i+1]]$RET[portfolio])
    dangqishouyi <- sum(ret) / sum(portfolio, na.rm = TRUE)
    junzhi <- dangqishouyi + junzhi
    jieguo1 <- c(jieguo1, dangqishouyi)
    principle <- (1 + sum(ret) / sum(portfolio, na.rm = TRUE)) * principle
    jieguo2 <- c(jieguo2, principle)
  }
  print(junzhi/3020)
  # return(principle)
  return(data.frame(jieguo1, jieguo2))
}
```