Event Study of *Private Placement*

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Note: This file contains 34 pages. It includes the cover page and contents (2 pages), the main report (20 pages), and an appendix (12 pages) which lists all the codes for this project. The codes are written in R and Stata. Apart from this report, we have uploaded all the supplementary files, including the data sets and R scripts, and Stata do files for replication of results. Please check them. Thanks.

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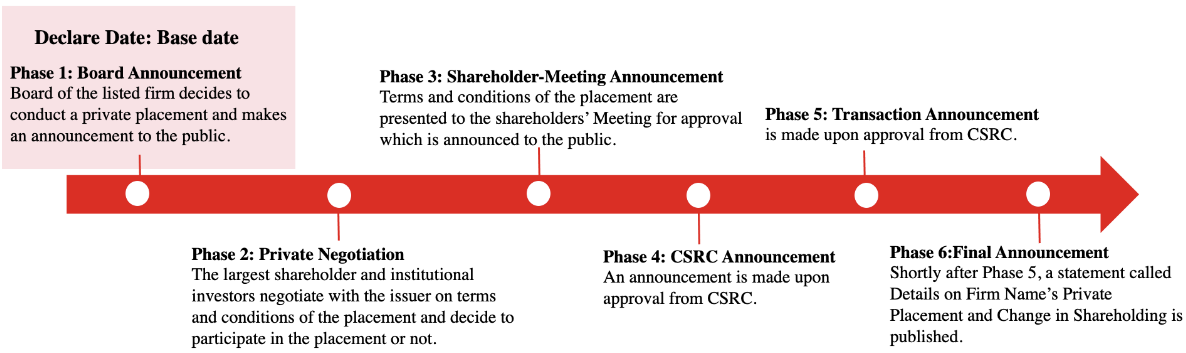
1 Introduction

Private placement, or private equity placement (PEP), is a popular way for publicly traded companies to finance capital. In China, PEPs are highly regulated by China Securities Regulatory Commission (CSRC). The participants of a PEP event cannot be more than 10 investors (China Securities Regulatory Commission, 2006), who may include institutional investors, wealthy individuals, controlling shareholders, and other legal investment organizations. Ordinary people are not allowed at most of time. Listed firms will offer discounts for investors to purchase the share at preferential prices, which are usually lower than the market prices. Before publicly issuing new equity to private placement investors, companies have to submit an application to CSRC. CSRC will determine whether the issuance reaches the basic requirements involving a suitable price level, legal lock-in periods, and so on. This application can be approved or denied. The following figure shows the general timeline of a private placement in China's Stock Market. According to the given dataset, the declare date represents the day on which the board of company's directors adopt the preliminary private placement plan, decide to conduct a private placement and declare the resolution publicly. Therefore, board announcement's declare date is the target period we are going to research.

Figure 1: The timeline of PEP process



Usually, before and after the preliminary PEP plan is announced publicly, the stock price will react to the announcement accordingly. Our research aims to investigate how the stock daily returns react to the events so that we can further examine whether the market is efficient. Apart from this, we will explore several significant factors to observe their relationships between excess return, such as market size, types of firms, leverage rates, discount rates, material asset reorganizations and getting approval from CSRC or not.

2 Literature Review

In the US, Hertzel and Smith in 1993 find a small and positive abnormal PEP announcement-period returns, which is 1.72%. Such positive announcement-effect phenomenon is also found in Japan (Kato & Schallheim, 1993) and Hong Kong (Wu et al., 2005). A majority of PEP research on China stock market only gives a general view that PEP has positive announcement-effect on stock returns in short run (He, 2010), which may due to the asset size, operating income, the proportion of the shares issued and so on. Less study focuses on the announcement-effect on different industries, such as, chemical, energy, technology industries. Thus, we would like to figure out how much abnormal returns is from 2010 to 2020 in mainland China and which versions of efficient or inefficient market does the stock market belongs to.

Some study indicates how the PEP's benefits and losses are anticipated by identities of investors in the US. For instance, PEP with positive announcement returns is because the investors participated are supposed to have superior information (Hertzel & Smith, 1993). They gain a deeper insight in firm's operation and even plays an important role in monitoring managers (Wruck, 1989). Besides, a research conducted by Zhang and Huang (Zhang & Huang, 2009) argues that the discount rate in PEP has negative relation with equity scale has no significant relation with companies' financial condition. We suspect during PEP periods there may exist potential relation between excess returns and discount rate, market size, leverage rate. Thus, we also take these factors into consideration in the Chinese stock market.

3 Data

3.1 Cleaning of Given Dataset

We start by cleaning the given dataset via the following steps:

1. Data Selection. As specified by the instruction, we delete ST stocks (Special Treatment, including *ST) and observations with `DeclareDate` before January 2010 or after December 2019. We also delete unnecessary features, such as `Objects`, `Comments`, etc. At the end of this step, we end up with 5730 entries with 9 features. This step is primary achieved by using `filter` function in Excel, which provides a handy tool to delete redundant observations and features.

2. Labelling. As specified by the instruction, stocks in the finance industry should be excluded from the dataset. Since industry is a potential factor affecting the abnormal return, we label each stock with its corresponding industry. The industry data is retrieved from CSMAR, and the labelling process is achieved by using `merge` function. The following table gives a summary of which industry the label stands for, as is set by China Securities Regulatory Commission (2012).

   Table 1: Industry Labels (as set by CSRC, 2012)

Label	**Industry**	**Label**	**Industry**
A	Agriculture, Forestry & Fishing	K	Real Estate
B	Mining	L	Rental
C	Manufacturing	M	Science
D	Utilities	N	Environment
E	Construction	O	Public Service
F	Retail	P	Education
G	Transportation	Q	Health Care
H	Accommodation and Food Services	R	Culture, PE, and Entertainment
I	IT	S	Others
J	Finance		

   Therefore, all the stocks labelled with "J" (i.e., the finance industry) are removed from the dataset.

3. Formatting. All dates in the dataset are formatted in the YYYY-MM-DD form, because we need to match different variables using dates.

3.2 Daily Stock Return

According to the instruction, we need to extract data starting from 10 days before the declaration date, to 10 days after the declaration date. We denote the declaration date as $t = 0$, and the whole period as $C(-10, 10)$. Since the trading days are not necessarily consecutive (weekends, holidays, etc.), we retrieve the 10 *trading day returns* before and after the declaration date $t = 0$. We use these trading days (in total 21, labelled as `dayrange` in codes) as a reference to other tables.

3.3 Related Variables

3.3.1 Systematic Risk β_i

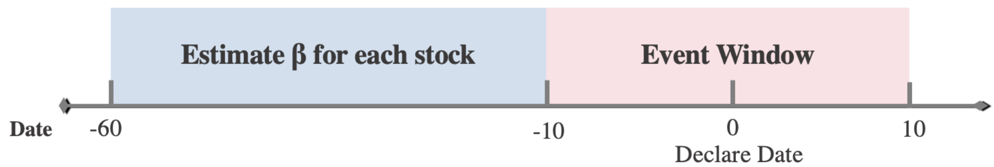
We directly retrieve data from CSMAR, where it is calculated by

$$\hat{\beta}_i = \frac{\sum_{t=1}^{T}(r_{it} - \bar{r}_{it})(r_{mt} - \bar{r}_{mt})}{\sum_{t=1}^{T}(r_{it} - \bar{r}_{it})^2}$$

This is the least squares estimator of the regression:

$$r_{it} = \alpha_i + \beta_i r_{mt} + \epsilon_{it}$$

For β_i on date t, CSMAR uses the daily returns of 50 trading days before date t for calculation (i.e., the sample size is 50) (CSMAR, 2020). In our study, for the total 21 days within the `dayrange`, instead of using the daily beta for each single date, we use the β_i at the very beginning of the `dayrange` (See figure below). This is because if we use the β_i for each single day, the beta might have incorporated the private placement information within the `dayrange` selected. Using the β_i at the beginning of the trading period effectively avoids this problem, thereby providing a more precise estimate of abormal return.



3.3.2 Market Return & Risk Free Rate

Based on the trading days `dayrange` specified when finding the daily returns, we retrieve r_m and r_f within the day range. We use CSI500 index return as the market return, and demand deposit interest rate (as used by CSMAR) as the risk-free rate.

3.3.3 Other Factors

Apart from the data analysis above, we further examine potential factors affecting the abnormal returns. Potential factors include the final outcome of private placement, the discount of private placement price (to be defined later), whether the PEP involves asset restructuring, the market value (i.e., the size of the company), the industry they are in, and the leverage rate. Similar as before, we match these factors with each observation, and divide them into groups to perform analysis. Observations with missing factors are omitted.

3.4 Special Cautions

1. Selection of observations: In China, Private Placements in general will go through the following process before declaration (CSRC, 2006):

   Table 2: Private Placement Process Before Declaration in China

Process	**Day**	**Announcement**
Due Diligence	$t-50$	/
Negotiation over Private Placement Plans	$t-30$	/
Drafting Private Placement Plans	$t-20$	Trading Suspension
Board Meeting and Declaration	t	Declaration

   It is noticeable that there could be 20 days for trading suspension. We therefore allow the maximum difference between two consecutive days in `dayrange` to be 20. In case the maximum difference becomes greater than 20 – that is, the stock was suspended from trading for more than 20 days before declaration, they will be removed from the dataset. This is because if a stock has been suspended from trading for too long before the declaration date (the extreme case could be more than half a year (China Vanke, 000002, for example)), the returns before trading suspension might not be able to incorporate the information of private placements.

2. Handling missing values: If any of the corresponding r_f, r_{mt} or β_i is missing, although unlikely, we remove the observation from the dataset.

The above procedure eventually leaves us with 1711 observations in the dataset. This is a sufficiently large dataset for further analysis.

4 Is the Market Efficient?

4.1 Method

To test the efficient market hypothesis, we plot the cumulative abnormal returns for the all the stock in A share. The abnormal return, $r_{abnormal}$, is calculated by

$$r_{abnormal} = r_{it} - \beta_i(r_{mt} - r_f) = \alpha_{it} + \epsilon_{it}$$

where
r_{it} is the return of stock i on date t;
β_i is the systematic risk of stock i compared to the market risk;
r_{mt} is the market return on date t;
r_f is the risk free rate;
α_{it} is the execess return of stock i on date t;
ϵ_{it} is the idiosyncratic risk of stock i on date t.

Note that we can diversify the idiosyncratic risk away by holding a well-diversified portfolio. This implies we can take the sum ϵ_{it} as 0 if we aggregate the abnormal returns of all stocks. Therefore, we can calculate the abnormal return $r_{abnormal}$ for every single observation over the 21 period. Then, we can calculate the average abnormal return from $C(-10, 10)$ as

$$r_{ab,t} = \frac{1}{N}\sum_{i=1}^{N} r_{ab,it}$$

where
$r_{ab,t}$ is the average abnormal return of the total 1711 observations on date t;
N is the total number of the observations;
$r_{ab,it}$ is the abnormal return of stock i on date t.

Other than this, we further calculate the market value weighted average abnormal return as

$$r_{ab,t(wgt)} = \sum_{i=1}^{N} wgt_{it} \times r_{ab,it}$$

where the weight wgt_{it} is

$$wgt_{it} = \frac{\text{Market Value of Stock } i \text{ on Date } t}{\sum_{j=1}^{N} \text{Market Value of Stock } j \text{ on Date } t}$$

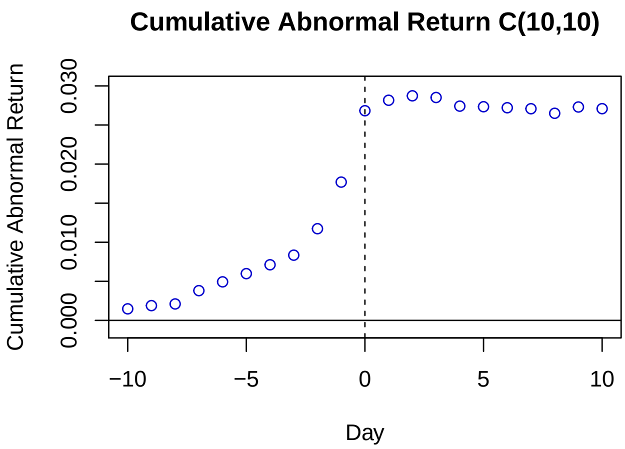
Finally, we calculate the cumulative abnormal return, $cumrt_T$, up to date T, as

$$cumrt_T = \prod_{t=1}^{T} (1 + r_{ab,t}) - 1$$

4.2 Results

The data analysis gives the following result. We see from the plot that the cumulative abnor-

Figure 2: Cumulative Abnormal Return



mal return shows an upward trend, and is consistently positive over this period. The most notable increase is on $t = 0$, i.e., the declaration date. The cumulative return then reaches a plateau, remaining stable at around 3% level.

When viewing the abnormal returns from a daily perspective, we have figure 3. We see from the plot that the simple average and weighted average returns have a similar trend, both peaking at $t = 0$, i.e., the declaration date. Our result shows that on average the daily abnormal return at the declaration date is around 0.9%, which is the highest over the 21 day period. To see whether the abnoraml returns are consistently positive, we use t- test to test this hypothesis. The summary statistics are given as follows: We see the daily abnormal returns for stocks with private placement plans are statistically greater than 0 over $C(-10, 10)$.

Figure 3: Daily Abnormal Return

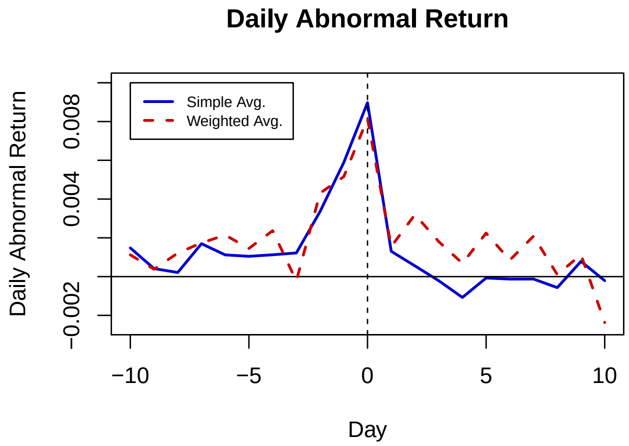


Table 3: Summary Statistics For Abnormal Returns

	Mean	Minimum	Maximum	t-statistic	p-value (one-sided)
Simple Average	0.13%	-0.11%	0.90%	2.529	0.01
Weighted Average	0.18%	-0.23%	0.81%	4.01	0.00

4.3 Implications

Our results suggest that from $C(-10, 10)$, stocks with private placement plans are expected to generate 3% excess return over the period, and the daily abnormal returns are statistically greater than 0. The most significant increase is $t = 0$, i.e., the declaration date, which is consistent with the *Announcement Effect*.

Our analysis also shows that the stock market is roughly in a semi-strong efficient condition. This is because we detect a immediate increase in the price on the announcement date and no obvious price drift after the announcement. We also find that the abnormal returns are consistently positive even before the declaration. Although the most notable increase is recorded on the declaration date, the abnormal returns before declaration are non-negligible. After the declaration date, however, the abnormal returns start to diminish, with the cumulative returns remaining stable.

To conclude, our analysis suggests that the market is in a **semi-strong** efficient condition, because the price immediately goes up after the declaration, and there is no slow drift in price after the announcement. The market has fully adjusted to the information. Overreaction is NOT detected in our analysis. However, our analysis is against the strong form of efficient market hypothesis. It is obvious that the market has incorporated some of the private placement information in ten days before the announcement, judging from the slow increase in the excess return before the announcement date. However, the sharp increase of abnormal return on the announcement date implies that the market has not incorporated all the private information. Therefore, the result proves that Chinese A share market is NOT in a strong efficient condition.

5 Further Inspection on Abnormal Return

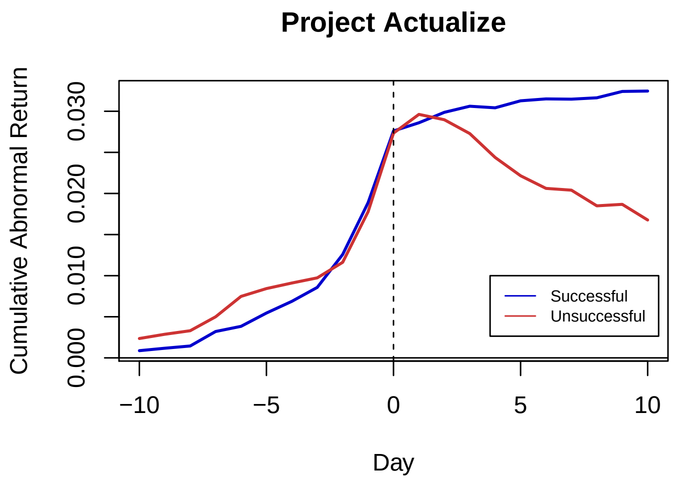
5.1 PEP Outcome

After companies submit application for PEP, CSRC will determine whether the application is approved or denied. If firms are approved, they can successfully finance capital from investors. Otherwise, they cannot finance in this way. We divided the data set into two groups. The first group contains events that successfully get approval from CSRC. The other contains events that are disapproved by CSRC.

5.1.1 Result

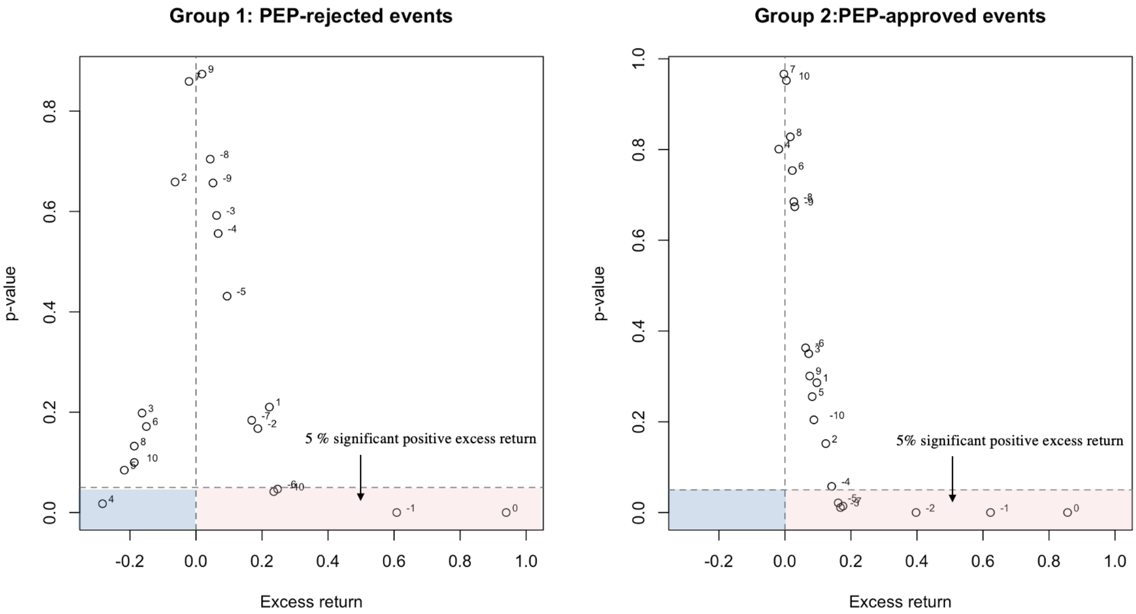
In terms of the market efficiency, if the market is semi-strong efficient, it is supposed to react to the new information quickly. The cumulative abnormal return should be immediately jump up after announcement without slow drift. The figure shows that there is a slow drift from [0, 10] of accumulative abnormal returns after the announcement date, which means market does not react to the public information immediately. It takes a long time for the market to fully react to the information. Arbitrage opportunities exist for a relatively long time. Thus, evidently, the market is inefficient in terms of semi-strong EMH version. For the events that are disproved, it takes one day after declare date to fully react to the information. Also, the curve presents a tendency to over-react to the market [1, 10]. It takes time for market to correct mistakes. Thus, it is also not efficient. Therefore, both groups reflect that stock market is inefficient in terms of semi-strong EMH version.

Figure 4: Cumulative Abnormal Return of Stocks with different PEP Outcoms



To further investigate whether the abnormal returns are related to firms' approval conditions by CSRC, we use some t-test to examine whether the excess return of each day is significantly different from zero. Two scatter diagrams (Figure 5) contain information of PEP-approved events (group 1) and PEP-rejected events (group 2) respectively. The label of each points represents date from -10 to 10, totally 21 days. Label "11" is the declare date. The horizontal dash line represent 5% significance level. The vertical dash line represents 0 expected excess return. The blue region represents negative excess return at 5 % significance level. The red region represents significantly positive excess return. Comparing two groups, we have the following findings:

Figure 5: P-value & Excess return for events with different PEP outcomes



1. During the event window, the group of events that are rejected by CSRC has more days with negative excess return, while the group of events that are approved generates positive excess return in almost all days.

2. During the event window, the approved events' group has 6 days with significantly positive excess return at 5% significance level. It does not have negative significant excess return. The disapproved events' group only has 4 days with significantly positive excess return. Moreover, in day 4, it has negative excess return at 5% significance level. This may be the result of market overreaction to the information.

3. For the approved events' group, it can already generate significant excess return 5 days before the declare date. However, for disapproved events' group, it starts to have significant excess return only 1 day before the declare date. The results indicate that the approved events' group can generate excess return for longer time. For both groups, the declare date and the day after declare date all have significant positive excess return.

5.1.2 Discussion

One of the reasons why market will over-react to the information for PEP-rejected events rely on that China stock market is highly supervised by CSRC. During the event window, ordinary investors do not have complete information whether this firm will be approved or not. They may be too over-confident about the firms such that these irrational investors drive up the stock prices and bring high excess return. However, the market will correct its mistake. After several days, the excess return quickly goes down.

It is remarkable that the group of events that are approved by CSRC generates positive excess return in almost every day. Based on the findings of present research, the evidence implies that regulators in China purposely select high quality companies with good investment opportunities, which potentially prevents low-quality companies from wasting capital resources. Due to the support to PEP of good companies, we can observe the group of PEP-approved firms have positive excess return at almost every day.

5.2 Discount of PEP

Usually, listed firms need to give a discounted price for the participants to purchase the shares. After purchasing these shares, investors will have a lock-in period for 12 or 36 months, which means during the period, they cannot trade these stocks in the market. Thus, this lock-in regulation brings uncertainty and risks for the investors. Such risks also determines the listed companies are supposed to give a discount to compensate the investors. Here, we would like to investigate whether discount rate will influence excess return or not. We calculate the discount rate based on the following formula. If discount rate is negative, it means investors buy the shares at a lower price than market price. If discount rate is positive, it means investors buy the shares at a higher price than the market value.

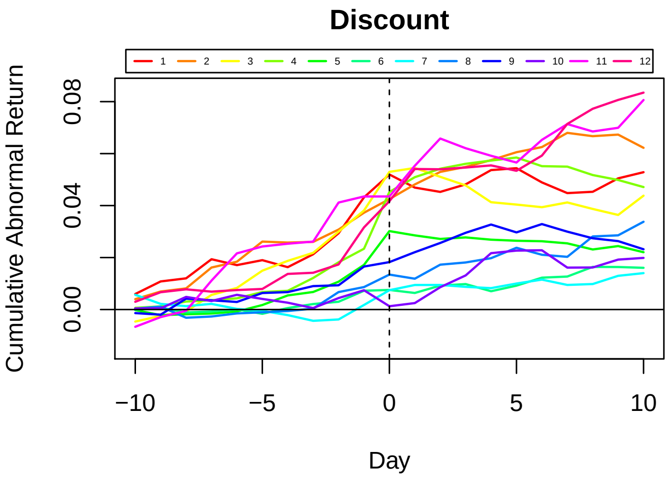
$$Discount\ rate = \frac{PEP\ Price - Market\ Price}{Market\ Price}$$

According to discount rate of each event, we divide the data set into 12 equally groups. The following figure shows the detailed interval of each group.

Figure 6: Twelve groups based on discount rate

5.2.1 Result

Figure 7: Cumulative Abnormal Return of Stocks with different PEP Outcoms



In terms of market efficiency, only group 7 indicates that the market is semi-efficient among the twelve groups. From [-10,-1], the average cumulative excess return is close to 0. At this period, the market does not react to the information. After day -1, the abnormal return drives up. It suggests that the information has been incorporated by the market. At the declare date, the cumulative abnormal returns reach the peak and fully adjust to the information and then remain stable. Hence, this curve indicates that the market is semi-strong efficient. However, the remaining curves either have slow drift after declare date or overreact to the information.

Thus, these results show that the market is inefficient in terms of semi-strong EMH version.

Then we test whether the excess return of each day is significantly different from zero at 5 % significance level for each group. Figure 8 (in next page) implies that if the discount rate is too high or too low, such as less than -0.4 and larger than 0.2, there is almost no days with significant excess return. Between [-0.4, 0.2], there are several days have positive significant excess return and these days are close to the declare date. It means PEP events with discount rate between [-0.4, 0.2] exist more potential opportunities to arbitrage and gain significant excess return.

5.2.2 Discussion

At most cases, the PEP stock prices should be lower than market prices to compensate the risk of investors. However, we find several companies sell the stocks at higher prices to investors than the market price. The reason behind is that CSRC regulates that issue price shall not be lower than 90% of the average stock price of the company in the 20 trading days prior to the benchmark pricing date(China Securities Regulatory Commission, 2006). So, probably, during the following days, due to the fluctuation of the stock market, the market prices decrease leading to lower prices than the PEP prices.

The results discovered in our study show that there is arbitrage opportunities if PEP prices are a little higher than market prices because the excess return is positive significant. We suspect that nowadays investors pay too much attention on PEP event that can give prices as low as possible to largely reduce their cost. Thus, firms with PEP prices close to market price does not attract investors. Actually, these firms may become high-quality companies in the future. Hence, they are not willing to provide low PEP prices for the investors before the declare date. Plus, the fluctuation of stock market makes the PEP prices a little higher than market. Therefore, there exists significant excess return by investing these firms.

5.3 Material Asset Reorganizations

The listed companies can improve their profit by injecting high-quality assets and integrating upstream and downstream enterprises through PEP. However, the choice of firms doing material asset reorganizations is not always rational. Even if sometimes it is sagacious for firms to do so, the ordinary investors may not understand the decision. To see whether events concerning material asset reorganizations are positive or negative signals in the stock market, we divide the dataset into two groups. Group 1 contains events that aim to achieve material asset reorganizations through PEP. Group 2 contains events whose goal is not material asset reorganizations.

5.3.1 Result

In terms of market efficiency, the red curve of group without reorganization shows the market is semi-strong efficient. At declare date, the curve immediately drives up and stays stable without any drift. It means market has fully adjusted to the information. However, for events concerning reorganizations (blue line), the market over-reacts to the information. Hence, in this scenario, the market is inefficient in terms of semi-strong MEH version.

We use some t-test to examine whether the excess return of each day is significantly different from zero at 5 % significance level. Two scatter diagrams (Figure 10) contain the information

Figure 8: P-value & Excess return for events with different discount rates

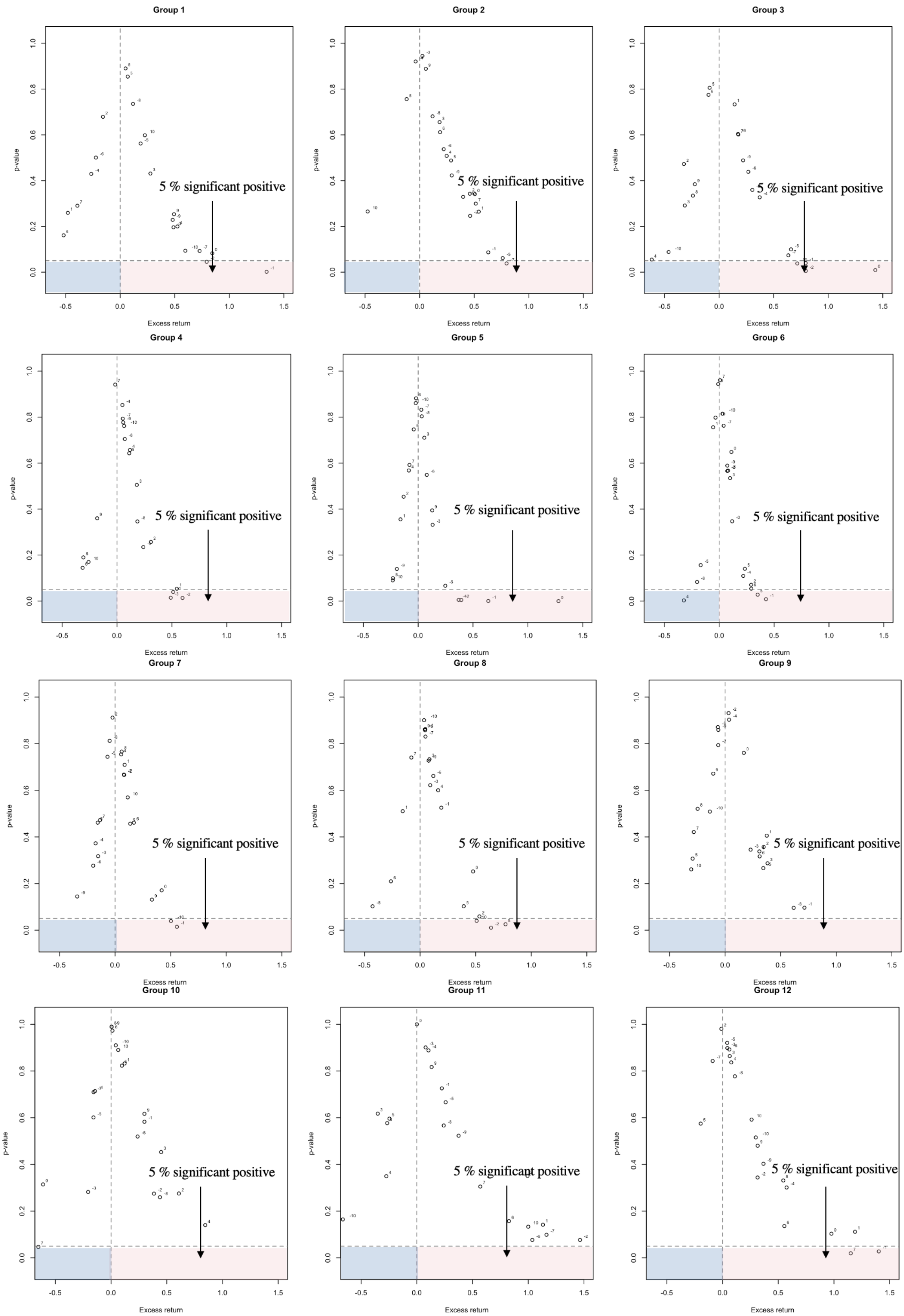
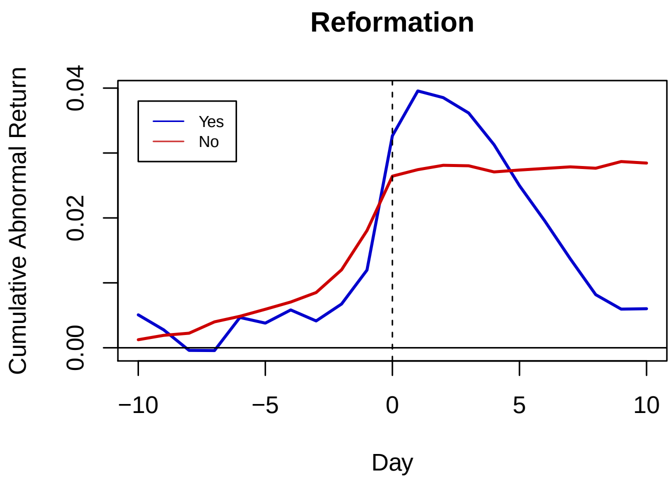
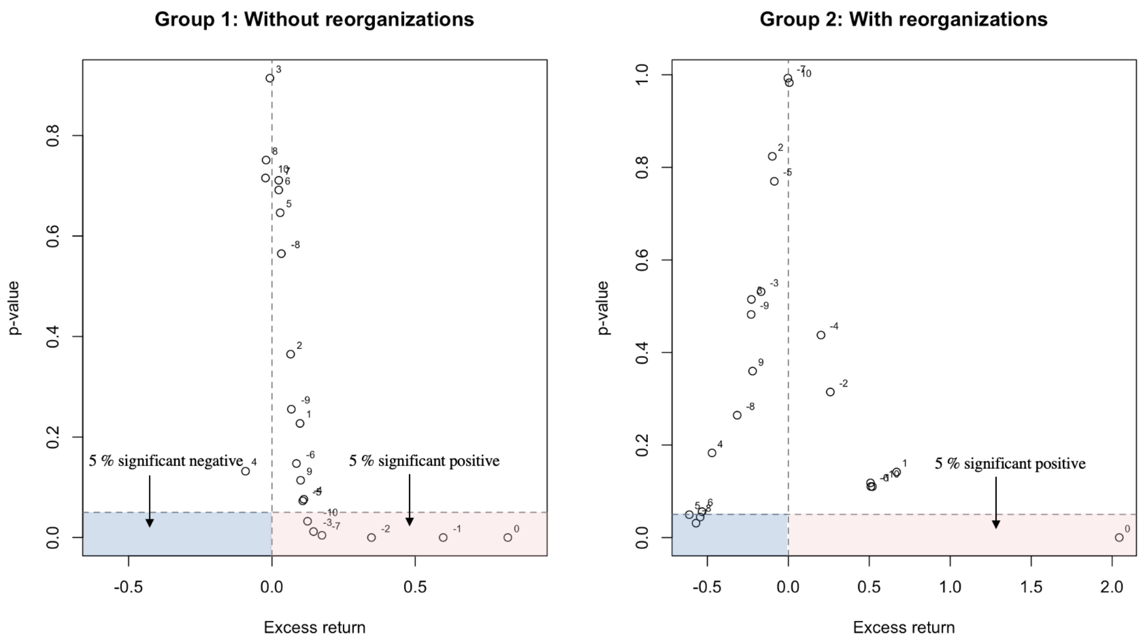


Figure 9: Cumulative Abnormal Return of Stocks with material asset reorganizations



of events without involving material asset reorganizations (group 1) and events involving material asset reorganizations (group 2) respectively. The label of each points represents date from -10 to 10, totally 21 days. Label "11"is the declare date. The horizontal dash line is 5% significance level. The vertical dash line means the expected excess return is 0. Comparing two groups, we have the following findings.

Figure 10: P-value & Excess return for events with or without reorganizations



1. During the event window, the group without material asset reorganizations generates positive excess return for majority days, while the group with material asset reorganizations has negative excess return for majority days.

2. During the event window, the group without material asset reorganizations has 6 days with significantly positive excess return at 5% significance level. It does not have negative significant excess return. However, the group with material asset reorganizations has 3

days with significant negative excess return. Surprisingly, it has only one day which is exactly the declare date with positive significant excess return.

3. For the group without material asset reorganizations, 3 days before the declare date, it can already generate significant excess return. For the group with material asset reorganizations, on the declare date, it starts to have significant excess return. The results indicate that the group without material asset reorganizations can generate excess return for longer time. For both groups, the declare date has significant positive excess return.

5.3.2 Discussion

We suspect the reason why market prefer events without material asset reorganizations is that such reorganizations will bring uncertainty and risks to the investors. After all, it is a material and important change for the listed companies. Whether the firm can benefit from the reorganization in the future or not is ambiguous for investors. For example, M&A is a common case of material asset reorganizations. For companies that are acquired, material asset reorganizations are beneficial to them as the quality of asset in the companies can be improved after that. Nevertheless, for listed companies the results are uncertain. The listed companies have to purchase the shares of acquired companies at higher prices. It is fairly costly, which will bring a negative signal for the stock market. Only in some rare cases, if the investors can clearly learn that such acquisition is obvious beneficial for the development of the listed companies, then this will bring positive signal to the market.

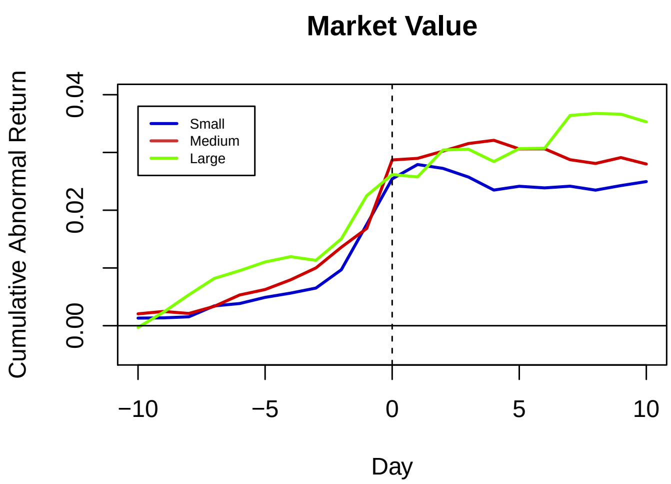
5.4 Market Value

Based on market value, we divide the stocks into three groups: 1. Small Value stocks, which has market value smaller than or equal to 50 million; 2. Medium Value stocks, which has market value between 50 million and 200 million; 3. High Value stocks, which has market value larger than 200 million.

5.4.1 Result

First, we plot the cumulative abnormal return for the three groups of stocks.

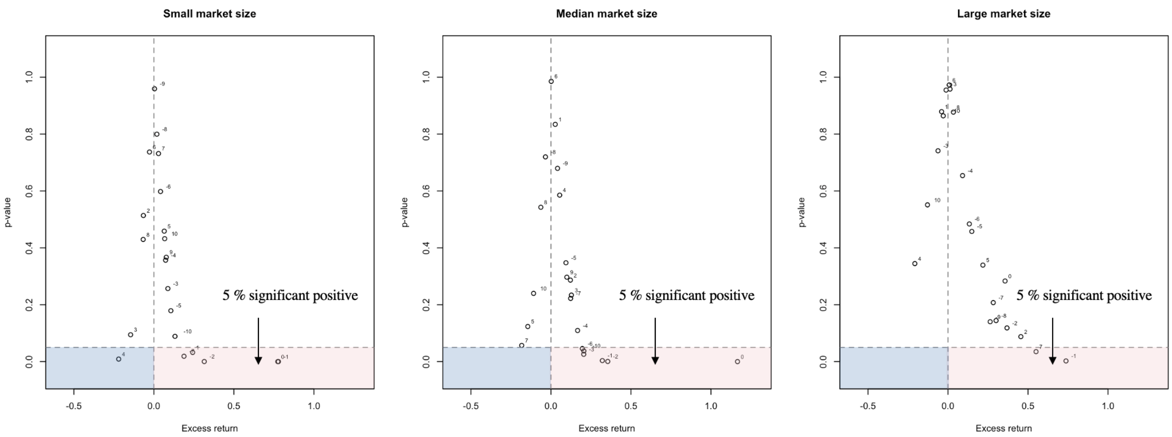
Figure 11: Cumulative Abnormal Return of Stocks with Different Market Value



According to Figure 12, we can see that the medium-value stocks are in the most efficient market among the three groups. Large-value stocks has the longest price drift, which shows that the price starts to increase before the announcement, and continue to increase after the announcement. This pattern shows that market react slowly but persistently to the news for large corporations, and the magnitude of reaction is significant. On the contrary, we can see from the plot that small-value stocks experience a huge increase on price on the announcement date. However, the price quickly start to fall after the announcement. This pattern show that market react fast to the news for small-value firms, but it tend to overreact. Thus, it takes some time for the market to correct the overreaction.

Then, we move on to test whether the three groups of stocks have positive or negative abnormal returns. The findings are as follows:

Figure 12: P-value & Excess return for events with different market values



1. The higher market value, the less date with significantly negative excess return. We can see that stocks with smallest market values (Group 1) has two days that generate significant negative return. Group 2 only has one, and group 3 has none.

2. Except for group 3, both group 1 and 2 has a significantly positive excess return on the announcement date (day 0). Group 3 has a excess return not significantly different from zero on day 0.

3. Medium-value stocks have the most number of significant positive excess return date, which is 6. While large-value stocks has the least number of significant positive excess return date, which is only 2.

5.4.2 Discussion

One possible explanation of the persistent increase in excess return of large-value companies even before the announcement is that bigger companies may have larger executive teams, which means the PEP information may known by more people in advance. Therefore, the risk of the outlet of private information is higher for large firms. This will lead to the increase in price before the announcement. Then, after the announcement, because people usually are very confident in the performance of large companies, the price continue to rise until it reaches the expectation the market. For small firms, as mentioned before, it is more likely for people to overreact when the information go public. However, comparing to large firms, people usually are not confident towards small firms. Therefore, the price quickly experience a sharp fall few days after the announcement.

The result that small and medium size firms are more likely to generate positive excess return implies that investors can focus more on the new information release for smaller firms. However, investors should also be cautious that small and medium size firms also have higher possibility to generate negative excess returns. This could be explained that market has a relatively more stable expectation on large firms than smaller firms. Therefore, a new information may not lead to a sharp increase or decrease in the return.

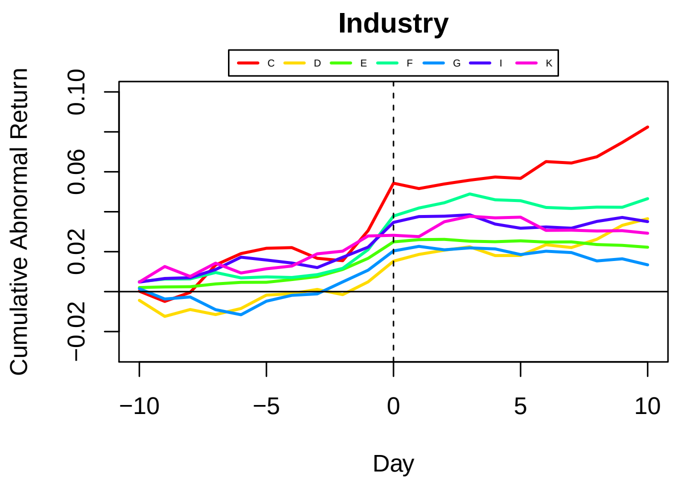
5.5 Industry

There are in total 17 industries, and the labels are explained in Table 1.

5.5.1 Result

We ignore the industries that has less than 30 firms that has PEP and plot the cumulative abnormal return.

Figure 13: Cumulative Abnormal Return of Stocks in Different Industries



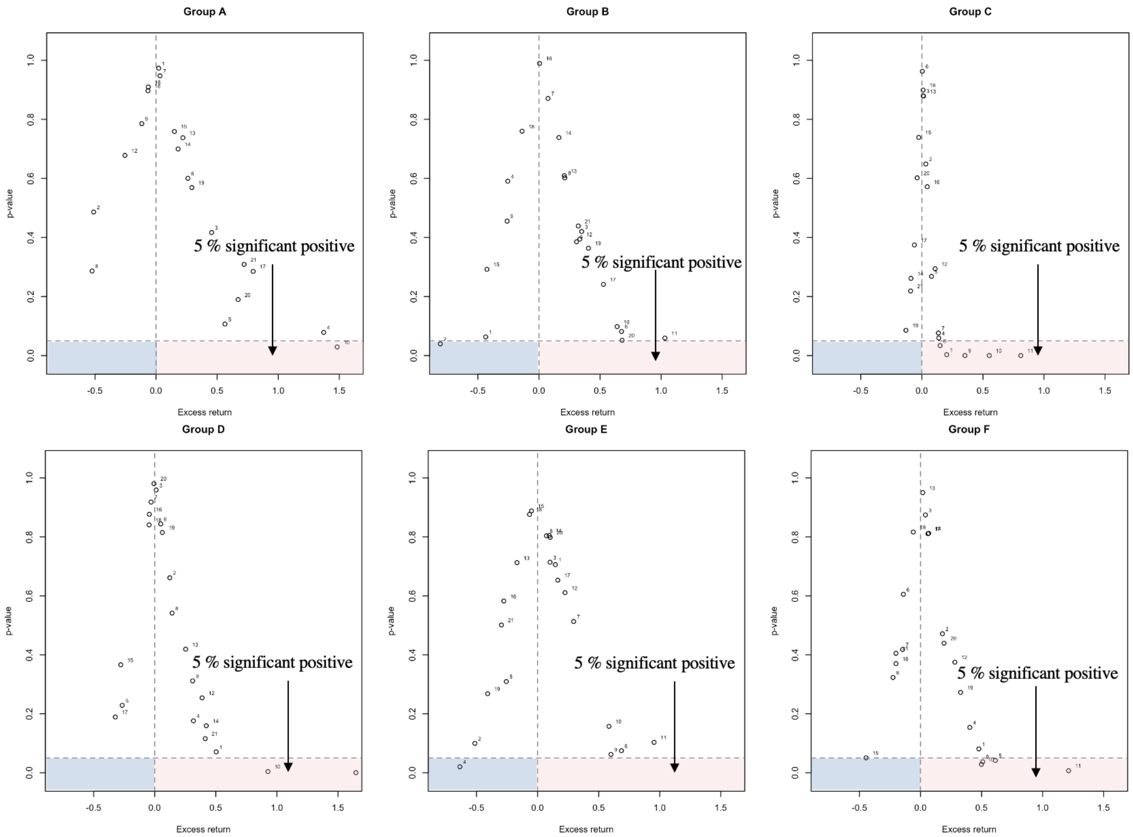
According to Figure 14, we can see that manufacturing industry (C) has the most sudden increase in excess return on the announcement date, and its excess return continue to increase after the announcement. Other industries generally follow the semi-strong efficient market hypothesis. Another point worth noticing is that for Utilities (D) and Transportation (G) companies, they both have negative cumulative excess return before the announcement date.

Then, we perform t-test for abnormal return on each day for each industry group. We find that different industry has very different pattern of abnormal returns:

1. Manufacture (C), Retail (F), and Transportation (G) industries have larger number of dates that generate positive excess returns than other industries. Manufacture industry has seven days, which are day 1 and day 7 to day 11. Retail industry has four days, which are day 5 and day 9 to day 11. Transportation industry also has four days, which are day 2, day 8, day 10, and day 13.

2. Transportation industry (G) is the industry that has the smallest number of dates that generate negative excess returns. It has three days: day 3, day 5, and day 17.
3. More than half of the dates for Environment (N) and Healthcare (Q) industries has negative excess return, although they are usually not very significant.

Figure 14: P-value & Excess return for events in different industries



5.5.2 Discussion

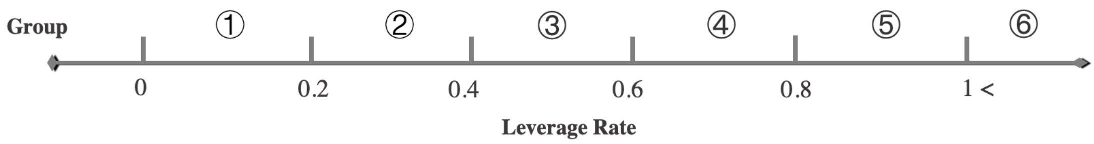
It is clear that Manufacture, Transportation and Utility stocks are not in a efficient market. One explanation is that manufacture firms are one of the most common firms in stock market, and they are usually in the key development area of the country. Therefore, people view the PEP for these firms as a good news and take it as a sign for the firm to expand. As a result, the excess return will sharply go up on the announcement date, and continue to go up after announcement.

Transportation and Utility are the fundamental industries for the country. Therefore, they may not have a high growth rate or growth potential. If these companies decide to do PEP, it may be due to their bad performance. This could explain the negative excess return before the PEP announcement date. However, PEP brings the hope for these companies to get back on track, causing an increase in the excess return for the stocks.
The reason why stocks in Environment and Healthcare industries have mostly negative excess return could be that these are more of a niche market, which experience turbulence and has a return of zero on average.

5.6 Leverage Rate

We divide the leverage rate into 6 groups. The following figure shows the detailed interval of each group:

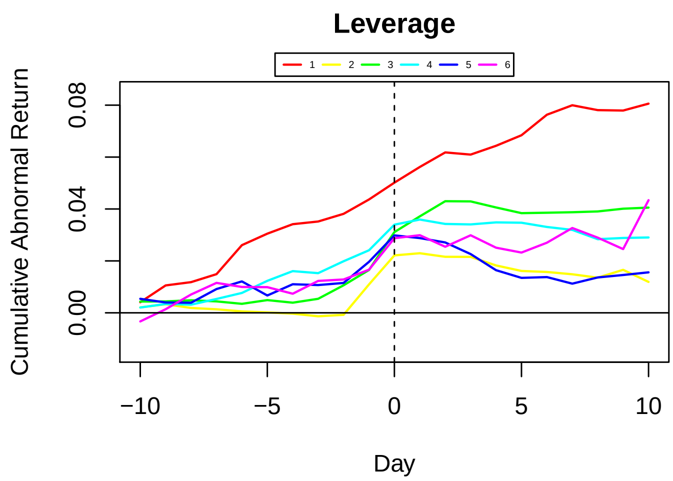
Figure 15: Six groups based on leverage rate



5.6.1 Result

First, we plot the cumulative abnormal return for the six groups of stocks:

Figure 16: Cumulative Abnormal Return of Stocks in Different Industries



The cumulative abnormal return for stocks with the smallest leverage rate is an upward sloping line. Then, we can see that most of stocks in other groups experience an increase in excess return on the announcement date, and then a decrease afterwards. These patterns clearly shows that the market is inefficient.

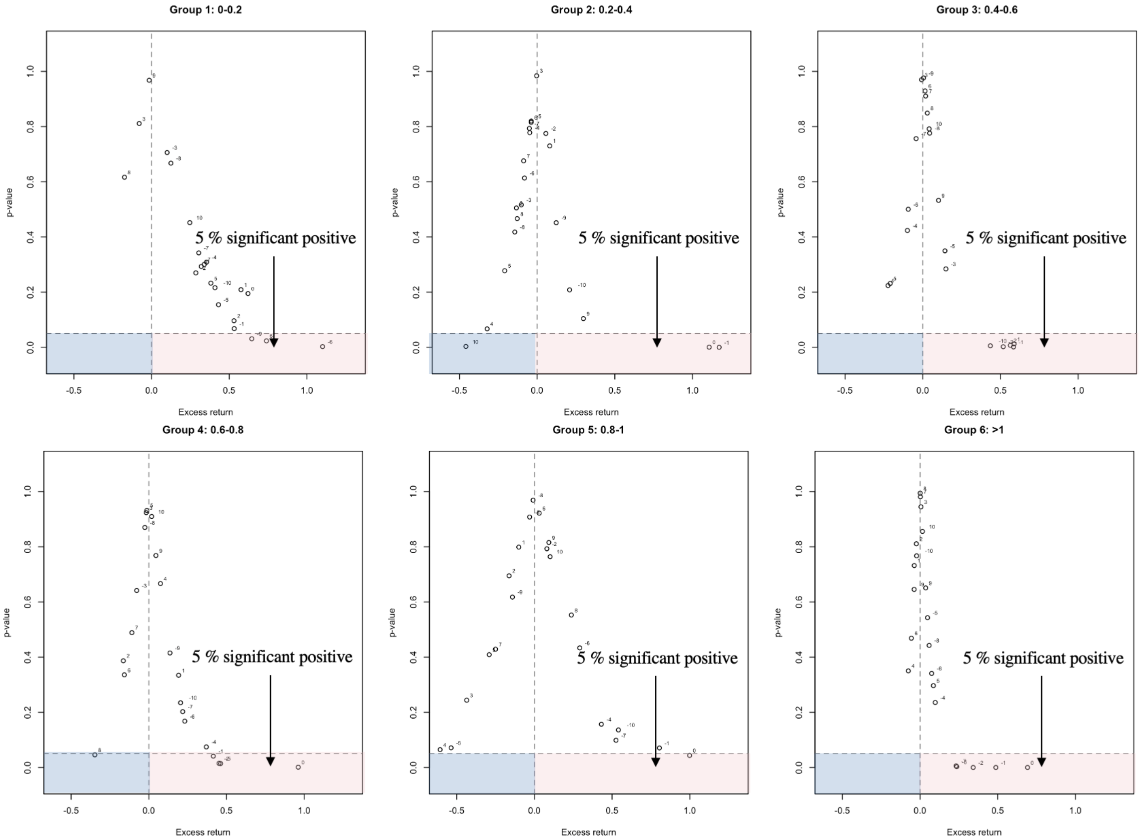
Second, we perform t-test for abnormal return on each day for each leverage group. The findings are as follows:

1. Stocks in all groups have a positive excess return on the announcement date. However, only in group 1 the excess return on the announcement date is not significant at 5% confidence level.

2. In general, firms that have higher leverage rate have more days that have significant positive excess return. For example, firms with leverage rate larger than 1 (Group 6) have five days of significant positive returns: day -7 and day -3 to day 0.

3. Group 1, 3 and 6 have all positive excess returns. The only few negative excess returns are not significantly different from zero.

Figure 17: P-value & Excess return Matrix for events with different leverage rates



5.6.2 Discussion

One possible explanation for the constant increase in cumulative excess return for smallest leverage rate is that, investors like this type of firms. Therefore, they continue to invest in these stocks, driving the price up in a relatively long period of time. This could also explain why only group 1 has a excess return no significantly different from zero on the announcement date. Generally, the most appropriate leverage ratio should be between 0.4 and 0.6. Companies with leverage ratio between 0.4 to 0.6 are in Group 3. We can see that Group 3 is in relatively the most efficient market, as the price stay roughly constant before and after the announcement, and a sudden increase on the announcement date.

The reason why higher leverage ratio is associated with more positive excess return is that, people may like companies with lower leverage more before PEP information. When the PEP information comes out, people will change the attitude towards those high leverage companies, therefore drive up the price and increase the excess return of those firms. The reasons above can also explain why Group 1, 3 and 6 have all positive excess returns respectively.

6 Conclusion

Our study suggests that the market is in a semi-strong efficient condition, because the price immediately goes up after the declaration, and there is no slow drift in price after the announcement. The market has fully adjusted to the information. After analyzing some important factors, we figure out that approved-events can generate significant positive excess return for longer days than disapproved-events. Also, PEP events with discount rate between [-0.4, 0.2] exist more potential opportunities to arbitrage and gain significant excess return. PEP events without material asset reorganizations have more days before the declare date to obtain excess return than PEP events concerning reorganizations. As for market values, the higher market value, the fewer dates with significantly negative excess return. In terms of industries, Manufacture, Retail, and Transportation industries have larger number of dates that generate positive excess returns than other industries. Apart from these, we also get the information that firms with higher leverage rate have more days that have significant positive excess return. The corresponding reasons are all given in the above discussion.

Reference

China Securities Regulatory Commission. (2006). Measures for the Administration of Securities Issuance by Listed Companies in China.

China Securities Regulatory Commission. (2012). A Guide for Industry Classification for Listed Companies.

CSMAR. (2020). *China Stock Market B Coefficient Database User Guide.* Shenzhen: CSMAR Data Technology.

He, L. (2010). Short-term Stock Performance of Private Placement of Listed Companies in China. *Journal of Shanxi Finance and Economics University.*

Hertzel, M. & R. Smith. (1993). Market Discounts and Shareholder Gains for Placing Equity Privately, *Journal of Finance*, *48*, 459–85.

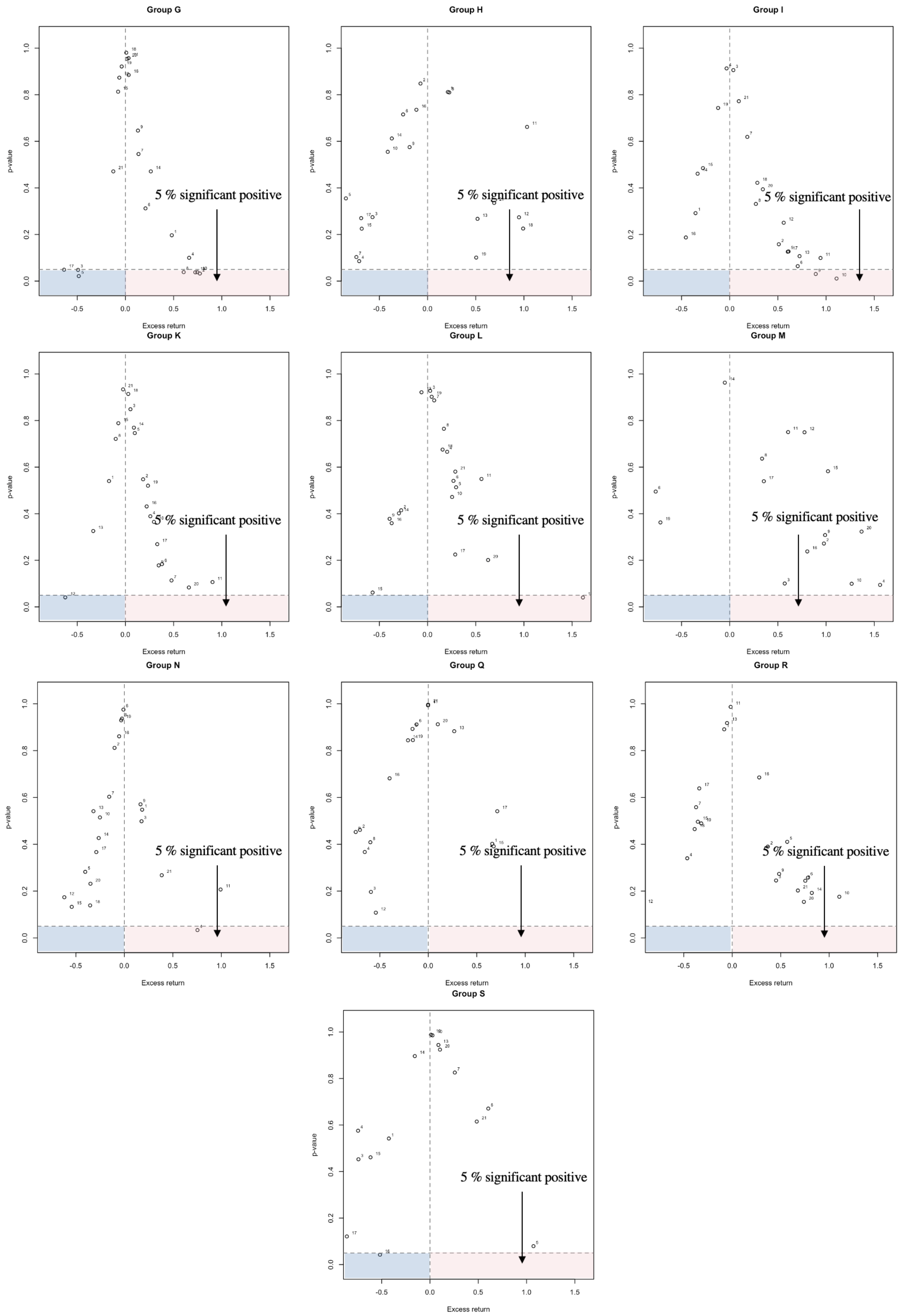
Kato, K. & J.S. Schallheim. (1993). Private Equity Financing in Japan and Corporate Grouping (Keiretsu). *Pacific Basin Finance Journal*, *1*, 287–307.

Wruck, K.H. (1989). Equity Ownership Concentration and Firm Value: Evidence from Private Equity Financings. *Journal of Financial Economics*, *23*, 2–38.

Zhang, L., & Huang, M. (2009). An Empirical Study on the Pricing of Private Placement in China's A-share market. *Science of Finance and Economics.*

Appendix 1: Figure 15 Cont'd

P-value & Excess return for events in different industries (Cont'd)



Appendix 2: Codes

```
dta=read.csv("dtanew.csv",header=T,encoding = "UTF-8")
label=read.csv("label.csv",header=T)
colnames(label)=c("stkcd","label")

label$label=substring(label$label,1,1)
colnames(dta)[1]="stkcd"

dataclean=merge(dta,label,by="stkcd")
fin=which(dataclean$label=="J")
dataclean=dataclean[-fin,]

dataclean$DeclareDate=as.Date(dataclean$DeclareDate, "%Y/%m/%d")

dataclean[dataclean==""]<-NA
dataclean$DeclareDate=format(dataclean$DeclareDate, "%Y-%m-%d")
class(dataclean$DeclareDate)
dataclean$DeclareDate=as.Date(dataclean$DeclareDate, "%Y-%m-%d")
idx=seq(1,nrow(dataclean),1)
dataclean=cbind(idx,dataclean)

beta1=read.csv("beta09-11.csv",header=T,encoding = "UTF-8")
beta2=read.csv("beta11-13.csv",header=T,encoding = "UTF-8")
beta3=read.csv("beta13-15.csv",header=T,encoding = "UTF-8")
beta4=read.csv("beta15-17a.csv",header=T,encoding = "UTF-8")
beta5=read.csv("beta15-17b.csv",header=T,encoding = "UTF-8")
beta6=read.csv("beta17-19a.csv",header=T,encoding = "UTF-8")
beta7=read.csv("beta17-19b.csv",header=T,encoding = "UTF-8")
beta8=read.csv("beta19-20.csv",header=T,encoding = "UTF-8")

beta=rbind(beta1,beta2,beta3,beta4,beta5,beta6,beta7,beta8)
colnames(beta)=c("Stkcd","tdate","betaval")
beta$tdate=as.Date(beta$tdate, "%Y-%m-%d")
beta=beta[order(beta$Stkcd,beta$tdate),]

rt1=read.csv("2009_2014_part1.csv",header=T,encoding = "UTF-8")
rt2=read.csv("2009_2014_part2.csv",header=T,encoding = "UTF-8")
rt3=read.csv("2009_2014_part3.csv",header=T,encoding = "UTF-8")
rt4=read.csv("2014_2018_part1.csv",header=T,encoding = "UTF-8")
rt5=read.csv("2014_2018_part2.csv",header=T,encoding = "UTF-8")
rt6=read.csv("2014_2018_part3.csv",header=T,encoding = "UTF-8")
rt7=read.csv("2018_2020_part1.csv",header=T,encoding = "UTF-8")
rt8=read.csv("2018_2020_part2.csv",header=T,encoding = "UTF-8")

rt=rbind(rt1,rt2,rt3,rt4,rt5,rt6,rt7,rt8)
colnames(rt)=c("Stkcd","tdate","return")
rt$tdate=as.Date(rt$tdate, "%Y-%m-%d")
rt=rt[order(rt$Stkcd,rt$tdate),]

rm=read.csv("zz500.csv",header=T,encoding = "UTF-8")
colnames(rm)=c("tdate","mreturn")
rm$tdate=as.Date(rm$tdate, "%Y-%m-%d")

riskfree=read.csv("riskfree.csv",header=T,encoding = "UTF-8")
colnames(riskfree)=c("tdate","rf")
riskfree$tdate=as.Date(riskfree$tdate, "%Y/%m/%d")
riskfree$tdate=format(riskfree$tdate, "%Y-%m-%d")
```

```r
riskfree$tdate=as.Date(riskfree$tdate, "%Y-%m-%d")

mktval1=read.csv("mktval09-11.csv",header=T,encoding = "UTF-8")
mktval2=read.csv("mktval11-13a.csv",header=T,encoding = "UTF-8")
mktval3=read.csv("mktval11-13b.csv",header=T,encoding = "UTF-8")
mktval4=read.csv("mktval13-15a.csv",header=T,encoding = "UTF-8")
mktval5=read.csv("mktval13-15b.csv",header=T,encoding = "UTF-8")
mktval6=read.csv("mktval15-17a.csv",header=T,encoding = "UTF-8")
mktval7=read.csv("mktval15-17b.csv",header=T,encoding = "UTF-8")
mktval8=read.csv("mktval17-19a.csv",header=T,encoding = "UTF-8")
mktval9=read.csv("mktval17-19b.csv",header=T,encoding = "UTF-8")
mktval10=read.csv("mktval19-20.csv",header=T,encoding = "UTF-8")

mktval=rbind(mktval1,mktval2,mktval3,mktval4,mktval5,mktval6,
             mktval7,mktval8,mktval9,mktval10)
colnames(mktval)=c("Stkcd","tdate","mktval")
mktval$tdate=as.Date(mktval$tdate, "%Y-%m-%d")
mktval=mktval[order(mktval$Stkcd,mktval$tdate),]

pr1=read.csv("pr09-14a.csv",header=T,encoding = "UTF-8")
pr2=read.csv("pr09-14b.csv",header=T,encoding = "UTF-8")
pr3=read.csv("pr09-14c.csv",header=T,encoding = "UTF-8")
pr4=read.csv("pr14-19a.csv",header=T,encoding = "UTF-8")
pr5=read.csv("pr14-19b.csv",header=T,encoding = "UTF-8")
pr6=read.csv("pr14-19c.csv",header=T,encoding = "UTF-8")
pr7=read.csv("pr14-19d.csv",header=T,encoding = "UTF-8")
pr8=read.csv("pr19-20.csv",header=T,encoding = "UTF-8")
pr=rbind(pr1,pr2,pr3,pr4,pr5,pr6,pr7,pr8)
colnames(pr)=c("Stkcd","tdate","pr")
pr$tdate=as.Date(pr$tdate, "%Y-%m-%d")
pr=pr[order(pr$Stkcd,pr$tdate),]


lb=read.csv("liab.csv",header=T,encoding = "UTF-8")

rst.rt=data.frame()
rst.beta=data.frame()
rst.rf=data.frame()
rst.rm=data.frame()
rst.mval=data.frame()

clname=paste("day",1:21,sep="")
clname=c("idx","stkcd",clname)

# core: matching results
for (i in 1:nrow(dataclean)){
  tmp.idx=which(rt$Stkcd==dataclean$stkcd[i] & rt$tdate==dataclean$DeclareDate[i])
  if (length(tmp.idx)==0){
    next
  }
  dayrange=rt[(tmp.idx-10):(tmp.idx+10),2]
  if (max(as.numeric(diff(dayrange)))>20){
    next
  }
  tmp.rt=rt[(tmp.idx-10):(tmp.idx+10),3]
  tmp=which(beta$Stkcd==dataclean$stkcd[i]&(beta$tdate %in% dayrange))
  tmp.beta=beta[tmp,3]
```

```
  if (length(tmp.beta)!=21){
    next
  }
  tmp0=which(mktval$Stkcd==dataclean$stkcd[i]&(mktval$tdate %in% dayrange))
  tmp.mv=mktval[tmp0,3]
  if (length(tmp.mv)!=21){
    next
  }
  tmp.a=which(riskfree$tdate %in% dayrange)
  tmp.rf=riskfree[tmp.a,2]
  if (length(tmp.rf)!=21){
    next
  }
  tmp.b=which(rm$tdate %in% dayrange)
  tmp.rm=rm[tmp.b,2]
  if (length(tmp.rm)!=21){
    next
  }

  tmp.rt=c(dataclean[i,1:2],tmp.rt)
  tmp.beta=c(dataclean[i,1:2],tmp.beta)
  tmp.mv=c(dataclean[i,1:2],tmp.mv)
  tmp.rf=c(dataclean[i,1:2],tmp.rf)
  tmp.rm=c(dataclean[i,1:2],tmp.rm)

  rst.rt=rbind(rst.rt,as.numeric(tmp.rt))
  rst.beta=rbind(rst.beta,as.numeric(tmp.beta))
  rst.mval=rbind(rst.mval,as.numeric(tmp.mv))
  rst.rf=rbind(rst.rf,as.numeric(tmp.rf))
  rst.rm=rbind(rst.rm,as.numeric(tmp.rm))
}

colnames(rst.beta)=clname
colnames(rst.mval)=clname
colnames(rst.rf)=clname
colnames(rst.rm)=clname
colnames(rst.rt)=clname

newbeta=rst.beta
for (i in 4:23){
  newbeta[,i]=newbeta[,3]
}


sub.beta=newbeta[,-c(1,2)]
sub.rt=rst.rt[,-c(1,2)]
sub.rf=rst.rf[,-c(1,2)]
sub.rm=rst.rm[,-c(1,2)]

sub.rt=100*sub.rt
abn=sub.rt-sub.beta*(sub.rm-sub.rf)

subdate=dataclean[,c(1,6)]

rst.abn=cbind(rst.rt[,c(1,2)],abn)
rst.abn=merge(rst.abn,subdate,by="idx")
```

```
trial.abn=rst.abn
sub.cpt=dataclean[,-c(3,6)]
trial.abn=merge(trial.abn,sub.cpt,by="idx")
trial.abn=cbind(trial.abn,avgmv)

sub.mval=rst.mval[,-c(1,2)]
avgmv=rowMeans(sub.mval)
mvptg=prop.table(as.matrix(sub.mval),2)
mvptg=cbind(rst.mval[,c(1,2)],mvptg) # weighted average return

colnames(trial.abn)[2]="Stkcd"
colnames(trial.abn)[24]="tdate"
newtrial=trial.abn
newtrial=merge(newtrial,pr,by=c("Stkcd","tdate"))
newtrial=newtrial[order(newtrial$idx),]
actpr=newtrial$pr
trial.abn=cbind(trial.abn,actpr)
discount=(trial.abn$Price-trial.abn$actpr)/trial.abn$actpr
trial.abn=cbind(trial.abn,discount)


colnames(lb)=c("Stkcd","year","lrate")
sub.df=rst.abn[,c(1,2,24)]
sub.df$DeclareDate=format(sub.df$DeclareDate, "%Y")
sub.df$DeclareDate=as.numeric(sub.df$DeclareDate)
lev=c()
for (i in 1:nrow(sub.df)){
  num=which((lb$Stkcd==sub.df$stkcd[i]) & (lb$year==(sub.df$DeclareDate[i]-1)) )
  if (length(num)==0){
    lev=c(lev,NA)
  }else{
    lev=c(lev,lb[num,3])
  }
}

trial.abn=cbind(trial.abn,lev)
rst.cplt=trial.abn[,-c(25)]

mat.alpha=rst.cplt[,3:23]
sum.rst=colSums(mat.alpha)
avg.alpha=sum.rst/nrow(mat.alpha)
avg.alpha=avg.alpha/100+1
cumrt=cumprod(avg.alpha)
plot(seq(-10,10,1),cumrt-1,xlab="Day",ylab="Cumulative Abnormal Return",
     main="Cumulative Abnormal Return C(10,10)",col="blue3",
     ylim=c(-0.001,0.03)) # cumulative return
abline(h=0)
abline(v=0,lty=2)


plot(seq(-10,10,1),avg.alpha-1,type="l",xlab="Day",ylab="Daily Abnormal Return",
     main="Daily Abnormal Return",ylim=c(-0.0025,0.01),lwd=2,col="blue3") # return
abline(h=0)
abline(v=0,lty=2)
lines(seq(-10,10,1),wgt.sum-1,col="red3",lwd=2,lty=2)
legend(-10,0.01,legend=c("Simple Avg.","Weighted Avg."),lty=c(1,2),
       col=c("blue3","red3"),lwd=2,cex=0.7)
```

```r
wgt=mvptg[,-c(1,2)]
wgt.rst=mat.alpha*wgt
wgt.sum=colSums(wgt.rst)/100+1
plot(wgt.sum,type="l")
lines(avg.alpha,type="l",col="red")

wgt.cumrt=cumprod(wgt.sum)
plot(wgt.cumrt) # wgt average

t.test(avg.alpha-1,mu=0,alternative = "greater")
t.test(wgt.sum-1,mu=0,alternative = "greater")

max(avg.alpha)
max(wgt.sum)
min(avg.alpha-1)
min(wgt.sum-1)

(avg.alpha-1)*100
cumrt

cptalpha=function(df){
  tmp.sum=colSums(df)
  tmp.avg=tmp.sum/nrow(df)
  tmp.avg=tmp.avg/100+1
  tmp.cumrt=cumprod(tmp.avg)
  tmp.cumrt=as.numeric(tmp.cumrt)
  return(tmp.cumrt)
}

# projectactualize

sub.proj1=rst.cplt[rst.cplt$ProjectActualize=="P6301",3:23]
sub.proj2=rst.cplt[rst.cplt$ProjectActualize=="P6302",3:23]
sub.proj1=sub.proj1[complete.cases(sub.proj1), ]
sub.proj2=sub.proj2[complete.cases(sub.proj2), ]
cumrt.proj1=cptalpha(sub.proj1)
cumrt.proj2=cptalpha(sub.proj2)
plot(seq(-10,10,1),cumrt.proj1-1,type="l",xlab="Day",
     ylab="Cumulative Abnormal Return",
     main="Project Actualize",col="blue3",lwd=2)
lines(seq(-10,10,1),cumrt.proj2-1,col="brown3",lwd=2)
abline(h=0)
abline(v=0,lty=2)
legend(3.8,1.01-1, legend=c("Successful","Unsuccessful"),col=c("blue3","brown3"),
       lty=1,cex=0.7)

# reformation

sub.ref1=rst.cplt[rst.cplt$ReformationSign=="Y",3:23]
sub.ref2=rst.cplt[rst.cplt$ReformationSign=="N",3:23]
sub.ref1=sub.ref1[complete.cases(sub.ref1), ]
sub.ref2=sub.ref2[complete.cases(sub.ref2), ]
cumrt.ref1=cptalpha(sub.ref1)
cumrt.ref2=cptalpha(sub.ref2)
plot(seq(-10,10,1),cumrt.ref1-1,type="l",xlab="Day",
     ylab="Cumulative Abnormal Return",
     main="Reformation",col="blue3",lwd=2)
```

```r
lines(seq(-10,10,1),cumrt.ref2-1,col="red3",lwd=2)
abline(h=0)
abline(v=0,lty=2)
legend(-10,0.038, legend=c("Yes","No"),col=c("blue3","brown3"),
       lty=1,cex=0.7)

# industry
coll1=rainbow(7)
industry=data.frame()
tmp.label=c("C","D","E","F","G","I","K")
tmp.label
for (i in 1:7){
  sub.itry=rst.cplt[rst.cplt$label==tmp.label[i],3:23]
  sub.itry=sub.itry[complete.cases(sub.itry), ]
  cumrt.itry=cptalpha(sub.itry)
  industry=rbind(industry,cumrt.itry)
}
plot(seq(-10,10,1),as.numeric(unlist(industry[1,]))-1,type="l",
     xlab="Day", ylab="Cumulative Abnormal Return",main="Industry",
     ylim=c(0.97-1,0.1),col=coll1[1],lwd=2)
for (i in 2:7){
  lines(seq(-10,10,1),as.numeric(unlist(industry[i,]))-1,col=coll1[i],lwd=2)
}
abline(h=0)
abline(v=0,lty=2)
legend("bottom", legend = tmp.label, inset=c(-0.2,1.02),
       xpd=TRUE, cex = 0.45, lty=1, col=coll1,horiz=T,lwd=2)


# discount

itvla=seq(-0.5,0.4,0.1)
itvlb=seq(-0.4,0.5,0.1)
itvl=cbind(itvla,itvlb)
itvl
discount=data.frame()
coll=rainbow(12)
for (i in 1:10){
  sub.disc=rst.cplt[(rst.cplt$discount>=itvl[i,1] & rst.cplt$discount<itvl[i,2]),3:23]
  sub.disc=sub.disc[complete.cases(sub.disc), ]
  cumrt.disc=cptalpha(sub.disc)
  discount=rbind(discount,cumrt.disc)
}
a=-0.5;b=0.5
sub.disc1=rst.cplt[(rst.cplt$discount< a),3:23]
sub.disc1=sub.disc1[complete.cases(sub.disc1), ]
cumrt.disc1=cptalpha(sub.disc1)
discount=rbind(cumrt.disc1,discount)
sub.disc2=rst.cplt[(rst.cplt$discount>0.5),3:23]
sub.disc2=sub.disc2[complete.cases(sub.disc2), ]
cumrt.disc2=cptalpha(sub.disc2)
discount=rbind(discount,cumrt.disc2)
plot(seq(-10,10,1),as.numeric(unlist(discount[1,]))-1,type="l",main="Discount",
     xlab="Day",ylab="Cumulative Abnormal Return",ylim=c(0.985-1,1.085-1),
     col=coll[1],lwd=1.5)
for (i in 2:12){
  lines(seq(-10,10,1),as.numeric(unlist(discount[i,]))-1,col=coll[i],lwd=1.5)
```

```
}
abline(h=0)
abline(v=0,lty=2)
legend("bottom", legend = seq(1,12,1), inset=c(-0.2,1.02),
        xpd=TRUE, cex = 0.4, lty=1, col=coll,horiz=T,lwd=1.5)

# market value
sub.mv1=rst.cplt[rst.cplt$avgmv<5000000,3:23]
sub.mv2=rst.cplt[(rst.cplt$avgmv>=5000000 & rst.cplt$avgmv<20000000),3:23]
sub.mv3=rst.cplt[(rst.cplt$avgmv>20000000),3:23]
sub.mv1=sub.mv1[complete.cases(sub.mv1), ]
sub.mv2=sub.mv2[complete.cases(sub.mv2), ]
sub.mv3=sub.mv3[complete.cases(sub.mv3), ]
cumrt.mv1=cptalpha(sub.mv1)
cumrt.mv2=cptalpha(sub.mv2)
cumrt.mv3=cptalpha(sub.mv3)
plot(seq(-10,10,1),cumrt.mv1-1,type="l",
     xlab="Day", ylab="Cumulative Abnormal Return",
     ylim=c(0.995-1,0.04),main="Market Value",col="blue3",lwd=2)
lines(seq(-10,10,1),cumrt.mv2-1,col="red3",lwd=2)
lines(seq(-10,10,1),cumrt.mv3-1,col="chartreuse",lwd=2)
abline(h=0)
abline(v=0,lty=2)
legend(-10,0.038, legend=c("Small","Medium","Large"),
       col=c("blue3","brown3","chartreuse"),
       lwd=2,cex=0.6)

# leverage
leverage=data.frame()
intervala=seq(0,1,0.2)
intervalb=seq(0.2,1,0.2)
intervalb=c(intervalb,100)
interval=cbind(intervala,intervalb)
coll2=rainbow(6)
for (i in 1:6){
  sub.lev=rst.cplt[(rst.cplt$lev>=interval[i,1] & rst.cplt$lev<interval[i,2]),3:23]
  sub.lev=sub.lev[complete.cases(sub.lev), ]
  cumrt.lev=cptalpha(sub.lev)
  leverage=rbind(leverage,cumrt.lev)
}
plot(seq(-10,10,1),as.numeric(unlist(leverage[1,])-1),
     type="l",main="Leverage",
     xlab="Day",ylab="Cumulative Abnormal Return",ylim=c(0.985-1,1.085-1),
     col=coll2[1],lwd=1.5)
for (i in 2:6){
  lines(seq(-10,10,1),as.numeric(unlist(leverage[i,]))-1,col=coll2[i],lwd=1.5)
}
abline(h=0)
abline(v=0,lty=2)
legend("bottom", legend = seq(1,6,1), inset=c(-0.2,1.02),
       xpd=TRUE, cex = 0.4, lty=1, col=coll2,horiz=T,lwd=1.5)
```

Stata Codes

```
 # Discount #
capture postclose pa
 postfile pa discountgroup str20 date mean p t
 using "C:\Users\117020205\Desktop\pa", replace
```

```
 foreach var in day1 day2 day3 day4 day5 day6 day7
 day8 day9 day10 day11 day12 day13 day14 day15
 day16 day17 day18 day19 day20 day21 {
 forvalues i = 1/12 {
 ttest `var'==0 if discountgroup == `i'
 post pa (`i') ("`var'") (r(mu_1)) (r(p)) (r(t))
 }
       }
postclose pa
use "C:\Users\117020205\Desktop\pa",clear
clear

# Market Value #
 capture postclose pa
 postfile pa mvgroup str20 date mean p t using
 "C:\Users\117020205\Desktop\pa", replace

 foreach var in day1 day2 day3 day4 day5
 day6 day7 day8 day9 day10 day11 day12 day13 day14
 day15 day16 day17 day18 day19 day20 day21 {
 forvalues i = 1/3 {
 ttest `var'==0 if mvgroup == `i'
 post pa (`i') ("`var'") (r(mu_1)) (r(p)) (r(t))
 }
       }
postclose pa
use "C:\Users\117020205\Desktop\pa",clear
clear

# Leverage Rate #
 capture postclose pa
 postfile pa levgroup str20 date mean p t
 using "C:\Users\117020205\Desktop\pa", replace

 foreach var in day1 day2 day3 day4 day5
 day6 day7 day8 day9 day10 day11 day12 day13 day14
 day15 day16 day17 day18 day19 day20 day21 {
 forvalues i = 1/7 {
 ttest `var'==0 if levgroup == `i'
 post pa (`i') ("`var'") (r(mu_1)) (r(p)) (r(t))
 }
       }
postclose pa
use "C:\Users\117020205\Desktop\pa",clear
clear


# Actualiztion #
 capture postclose pa
 postfile pa PojectActualiztion str20
 date mean p t using "C:\Users\117020205\Desktop\pa", replace

 foreach var in day1 day2 day3 day4 day5 day6 day7
 day8 day9 day10 day11 day12 day13 day14 day15
 day16 day17 day18 day19 day20 day21 {
 forvalues i = 0/1 {
 ttest `var'==0 if ProjectActualize == `i'
```

```
 post pa (`i') ("`var'") (r(mu_1)) (r(p)) (r(t))
 }
       }
postclose pa
use "C:\Users\117020205\Desktop\pa",clear
clear


# Reformation #
 capture postclose pa
 postfile pa Reformation str20 date mean p t
 using "C:\Users\117020205\Desktop\pa", replace

 foreach var in day1 day2 day3 day4 day5 day6
 day7 day8 day9 day10 day11 day12 day13 day14
 day15 day16 day17 day18 day19 day20 day21 {
 forvalues i = 0/1 {
 ttest `var'==0 if ReformationSign == `i'
 post pa (`i') ("`var'") (r(mu_1)) (r(p)) (r(t))
 }
       }
postclose pa
use "C:\Users\117020205\Desktop\pa",clear
clear


# Industry #
 capture postclose pa
 postfile pa Industry str20 date mean p t
 using "C:\Users\117020205\Desktop\pa", replace

 foreach var in day1 day2 day3 day4 day5 day6
 day7 day8 day9 day10 day11 day12 day13 day14
 day15 day16 day17 day18 day19 day20 day21 {
 forvalues i = 1/17 {
 ttest `var'==0 if industry == `i'
 post pa (`i') ("`var'") (r(mu_1)) (r(p)) (r(t))
 }
       }
postclose pa
use "C:\Users\117020205\Desktop\pa",clear
clear
```

Codes for Factor Analysis

```r
library("stringr")


su = read.csv("success.csv")
re = read.csv("reformation.csv")


su1 = su[su$actualization==0,]
su2 = su[su$actualization==1,]

re1 = re[re$reformation==0,]
re2 = re[re$reformation==1,]
head(re1)
```

```r
#finished
par(mfrow=c(1,2))
b = su1$date
su1$date = as.numeric(str_extract_all(b,"[0-9]{1,3}"))
su1=su1[order(su1$date),]
plot(su1$Excess,su1$p,ylab ="p-value",xlab="Excess return",
     main="Group 1: PEP-rejected events",xlim=c(-0.3,1))
abline(h=0.05,lty=2,col="grey45")
abline(v=0,lty=2,col="grey45")
text(x=su1$Excess, y=su1$p, labels = (su1$date-11),
     cex = 0.6, adj = c(-1.1,-0.2))


b = su2$date
su2$date = as.numeric(str_extract_all(b,"[0-9]{1,3}"))
su2=su2[order(su1$date),]
plot(su2$Excess,su2$p,ylab ="p-value",
     xlab="Excess return",
     main="Group 2: PEP-approved events",xlim=c(-0.3,1))
abline(h=0.05,lty=2,col="grey45")
abline(v=0,lty=2,col="grey45")
text(x=su2$Excess, y=su2$p, labels = (su2$date-11),
     cex = 0.6, adj = c(-1.1,-0.2))

head(re)

par(mfrow=c(1,2))
b = re1$date
re1$date = as.numeric(str_extract_all(b,"[0-9]{1,3}"))
re1=re1[order(re1$date),]
plot(re1$Excess,re1$p,ylab ="p-value",
     xlab="Excess return",
     main="Group 1: Without reorganizations",xlim=c(-0.6,0.9))
abline(h=0.05,lty=2,col="grey45")
abline(v=0,lty=2,col="grey45")
text(x=re1$Excess, y=re1$p,
     labels = (re1$date-11),cex = 0.6, adj = c(-1.1,-0.8))


b = re2$date
re2$date = as.numeric(str_extract_all(b,"[0-9]{1,3}"))
re2=re2[order(re2$date),]
plot(re2$Excess,re2$p,ylab ="p-value",
     xlab="Excess return", main="Group 2: With reorganizations")
#xlim=c(-0.6,1)
abline(h=0.05,lty=2,col="grey45")
abline(v=0,lty=2,col="grey45")
text(x=re2$Excess, y=re2$p,
     labels = (re2$date-11),cex = 0.6, adj = c(-1,-0.8))


di = read.csv("discount.csv")
b = di$date
di$date = as.numeric(str_extract_all(b,"[0-9]{1,3}"))
a = c("Group 1","Group 2","Group 3","Group 4",
      "Group 5","Group 6","Group 7","Group 8",
      "Group 9","Group 10","Group 11","Group 12")
par(mfrow=c(1,3))
```

```
for (i in 1:12){
  data1 = di[di$discountgroup==i,]
  plot(data1$Excess,data1$p,ylab ="p-value",xlab="Excess return",
       main=c(a[i]),xlim=c(-0.6,1.5),ylim=c(-0.05,1.03))
  abline(h=0.05,lty=2,col="grey45")
  abline(v=0,lty=2,col="grey45")
  text(x=data1$Excess, y=data1$p,
       labels = (data1$date-11),cex = 0.6, adj = c(-1.1,-0.8))

}


In = read.csv("industry.csv")
b = In$date
In$date = as.numeric(str_extract_all(b,"[0-9]{1,3}"))
a = c("Group A","Group B","Group C",
      "Group D","Group E","Group F","Group G",
      "Group H","Group I","Group K","Group L",
      "Group M","Group N","Group P",
      "Group Q","Group R","Group S")
par(mfrow=c(1,3))
for (i in 1:17){
  data1 = In[In$industry==i,]
  plot(data1$Excess,data1$p,
       ylab ="p-value",xlab="Excess return",
       main=c(a[i]),xlim=c(-0.8,1.6),ylim=c(-0.02,1.05))
  abline(h=0.05,lty=2,col="grey45")
  abline(v=0,lty=2,col="grey45")
  text(x=data1$Excess, y=data1$p,
       labels = data1$date,cex = 0.6, adj = c(-1.1,-0.8))

}

si = read.csv("size.csv")
head(si)
b = si$date
si$date = as.numeric(str_extract_all(b,"[0-9]{1,3}"))

a = c("Small market size",
      "Median market size", "Large market size")
par(mfrow=c(1,3))
for (i in 1:3){
  data1 = si[si$mvgroup==i,]
  plot(data1$Excess,data1$p,ylab ="p-value",xlab="Excess return",
       main=c(a[i]),xlim=c(-0.6,1.3),ylim=c(-0.05,1.1))
  abline(h=0.05,lty=2,col="grey45")
  abline(v=0,lty=2,col="grey45")
  text(x=data1$Excess, y=data1$p,
       labels = (data1$date-11),cex = 0.6, adj = c(-1.1,-0.8))

}

le = read.csv("lev.csv")
head(le)
b = le$date
le$date = as.numeric(str_extract_all(b,"[0-9]{1,3}"))
a = c("Group 1: 0-0.2", "Group 2: 0.2-0.4",
```

```
      "Group 3: 0.4-0.6", "Group 4: 0.6-0.8",
      "Group 5: 0.8-1","Group 6: >1")
par(mfrow=c(1,3))
for (i in 1:6){
  data1 = le[le$levgroup==i,]
  plot(data1$Excess,data1$p,ylab ="p-value",xlab="Excess return",
       main=c(a[i]),xlim=c(-0.6,1.3),ylim=c(-0.05,1.1))
  abline(h=0.05,lty=2,col="grey45")
  abline(v=0,lty=2,col="grey45")
  text(x=data1$Excess, y=data1$p,
       labels = (data1$date-11),cex = 0.6, adj = c(-1.1,-0.8))

}
```