Prediction of the Streak-broken Day for China's IPO Stocks

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Abstract

"Hit new stock" is an interesting and exciting phenomenon in China's stock market. To assist investors in making wise decision, we conduct our research by applying two models, static model and dynamic model, into China's IPO stock market from the beginning of 2014 to the end of 2016. From the empirical evidence given by the static model, factors such as Turnover Rate, Asset Per Share, Success Rate in purchasing, etc. have significant influences on the length of the increasing streak after IPO. Sectors, market stages, as well as industries may also play significant roles in deciding how long could this streak last. Then we incorporate our results from the static model into the dynamic model, and forecast the probability that the streak breaks on the next trading day. Finally, we compare our prediction-based trading strategy with simple Buy-and-Hold strategy, and get different expected relative gain or loss levels in different market scenarios.

Keywords

Increasing Streak, China's IPO Stocks, Turnover Rate, APS, Probit Model, Buy-and-Hold

Introduction

In China, an interesting and exciting phenomenon in stock market is called "hit new stock", which means either institutional or retail investors draw lots to buy newly issued stocks from upcoming IPO companies.

Due to the regulation of Chinese Securities Regulatory Commission (CSRC), stocks in China have price limit in daily trading. For the first trading day, the price limit is 44%, and for the rest trading days, the price limit is 10%, which means the price of individual stock could have a maximum percentage increase or decrease of 10% on the current trading day compared to the close price of the last trading day.

The probability to draw lots successfully is very low. However, once being able to purchase some shares of the new issued stocks, one can usually expect a streak of increase for weeks or even a month. The price of the stock could be tripled and even ten folded within few days! However, once the increasing streak breaks, it is usually followed by days of consecutive decrease in price, and investors holding the stocks may encounter heavy loss since it is not easy for them to sell stocks when the price drops dramatically, especially when the price touches lower price limit where the sellers are anxiously waiting in line for buyers to buy. So, what seems a safer strategy is to sell the stock earlier before the increasing streak breaks. However, one may loss a great chance to earn more money due to selling too early. So, the timing issue of when to sell the stocks at the most proper time is essential to investors to maximize their profits.

In our paper, we are trying find out how long can this increasing streak last.

Literature Review

The reason behind this interesting phenomenon in China's stock market is that IPO stocks are usually underpriced. It is a common phenomenon around the world. [1] An IPO stock is considered to be underpriced when the offer price is lower than the price of its first trading day. In China, due to the regulation of price limit on each trading day, the true market value cannot be reflected until the increasing streak breaks. [2] However, a stock is usually only underpriced temporarily because the laws of supply and demand will eventually drive it toward its intrinsic value.

So, what are the reasons for the underpricing issue of IPO stocks? Rock and Kevin (1986) state that the existence of a group of investors who has superior information over other investors makes the offering firm price the shares at a discount in order to guarantee that the uninformed investors purchase the issue. [3] Ruud, Judith S. (1993) find that the initial returns following IPOs show a negative skewed distribution, and underwriter price support may account for the skewed distribution and hence the phenomenon of positive average initial IPO returns. [4] Booth, James R., and Lena Chua (1996) develop an explanation that the issuer's demand for ownership dispersion creates an incentive to underprice. Because promoting oversubscription by underpricing allows broad initial ownership, which in turn reduces the required return to investors. [5] The same answer is given by Brennan, Michael J., and Julian Franks (1997) who show that underpricing is used to ensure oversubscription and rationing in the share allocation process so as to allow owners to discriminate between applicants for shares and to reduce the block size of new shareholdings. [6] Lowry, Michelle, and Susan Shu (2002) examine and confirm the litigation-risk hypothesis which states that high litigation-risk of the firm causes underpricing of its IPO stock. [7]

Underpricing issue in China may be caused by additional reasons due to its special market stage and regulations. Chan, Kalok, Junbo Wang, and KC John Wei (2004) find that the underpricing of A-share IPOs is positively related to the number of days between the offering and the listing and the number of stock investors in the province from which the IPO comes, and negatively related to the number of shares being issued. [8] Ting, Y. U., and Yiu Kuen Tse (2006) use IPO data for online fixed-price offerings from November 1995 to December 1998 to show that the winner's curse hypothesis is the main reason for the high IPO underpricing in China. [9] Hao, Xiangchao, Jing Shi, and Jian Yang (2014) conclude that the bank–firm relationship reduces the degree of IPO underpricing. Higher credit quality or better the relationship between politically unconnected firms and banks has a more positive impact on mitigating IPO underpricing. [10]

However, most of the papers mentioned above document the relation between underpricing and other factors qualitatively. They don't give us a quantitative method to measure how much the underpricing would be, given factors discussed in their papers. Also, the "hit new stock" phenomenon emerged only in the past few years after new IPO regulations were enforced. Due to the limitation of the number of IPO stock and stable stock market environment in the past few years, plus the slight chance of purchasing IPO stock successfully, very few researches have been done in this field. However, with more stocks going public and the "hit new stock" trend becoming more popular, investors feel it is more and more necessary to find out the quantitative degree of overpricing so as to help them make wise investment decisions. Our paper takes the initiative to conduct the research in this field.

Data Description

Since Jan 1st 2014, Chinese Securities Regulatory Commission set an upper limit of 44% of increase for first trading day of new issued stocks. So, we selected 575 individual stocks whose first trading days fall into the time period from Jan 1st 2014 to Dec 31st 2016. We collected basic information of each individual stock and daily market transaction information of each stock from the day it went public to the day when the increasing streak broke.

Table 1 shows how many stocks have an increasing streak of certain days. For example, there are 7 stocks didn't even touch the 44% price limit on their first trading day, some declining from IPO prices while others increasing less than 44%; there are 15 stocks snaps their increasing streak on their second trading day; only one stock has an increasing streak as long as 30 days.

Table 1

Increasing Streak (days)	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
Number of Individual Stocks	7	15	14	9	21	29	30	34	30	35
Increasing Streak (days)	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**
Number of Individual Stocks	40	40	37	21	41	31	23	17	20	20
Increasing Streak (days)	**20**	**21**	**22**	**23**	**24**	**25**	**26**	**27**	**28**	**29**
Number of Individual Stocks	16	12	8	9	2	6	3	1	1	2
Increasing Streak (days)	**30**									
Number of Individual Stocks	1									

Since our prediction is based all the information available before the end of the first trading day, if the we already know that the streak breaks on the first day, there is no need for any prediction. So, in our following work, we exclude from our dataset those 7 stocks whose increasing streaks are 0. Thus 566 individual stocks are left in our dataset.

Table 2 shows the minimum, maximum, mean and quantile information of the days of increasing streak for all individual stocks in the dataset.

Table 2

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
1	7	11	11.72	15	30

Figure 1 depicts a graph of the distribution of the days of increasing streak.

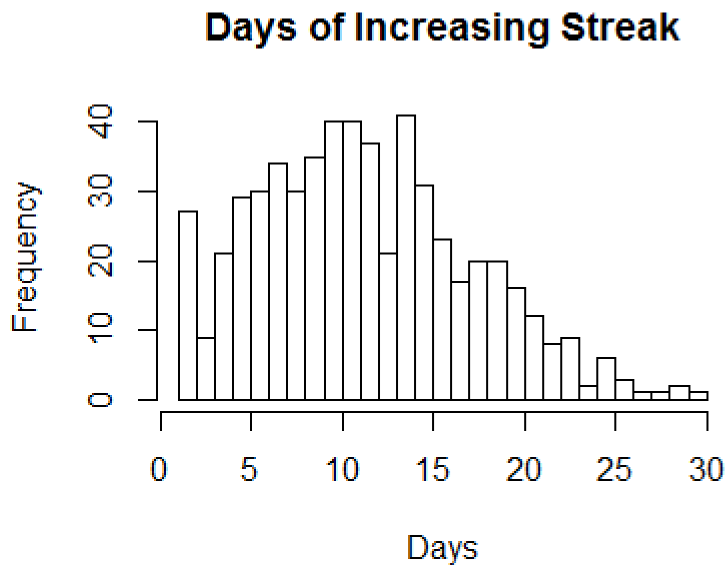

Figure 1

From Table 2 and Figure 1, we can see that the distribution of the days of increasing streak is right-skewed, which means for a few stocks, they have extremely longer increasing streak than other stocks.

During the 3-year time period from which we select the data, China's stock market experienced both bullish market and bearish market as well as policy and regulation adjustments. We plot the relation between days of increasing streak and IPO date in Figure 2.

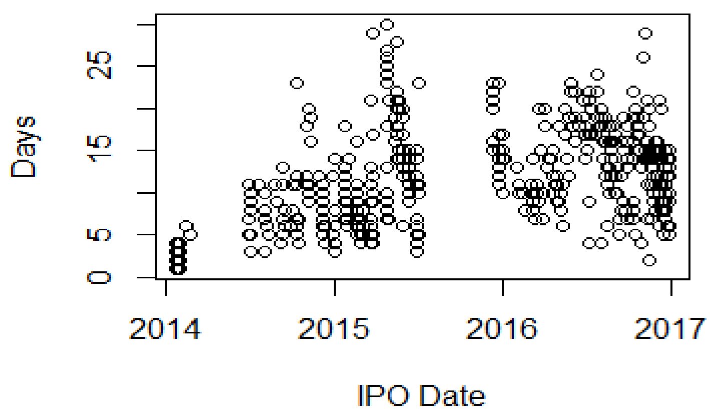

Figure 2

From Figure 2, we can see that there are twice IPO suspensions: one was in the beginning of 2014; the other was in the end of 2015. And in the year 2015, China's stock market encountered the historical turning point where the stock market turned from bullish to bearish. The volatility of the days of increasing streak after this point was significantly higher than it was before. So, based on the results of our observation, we divide the whole time period into 5 stages. And Table 3 summarizes the information of days of increasing streak for stocks in each stage.

Table 3

	Time Period	Number of Stocks	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
Stage 1	2014/01/01 ~ 2014/06/01	43	1	1	2	2.488	4	6
Stage 2	2014/06/01 ~ 2015/03/01	120	3	6.75	8	8.867	11	23
Stage 3	2015/03/01 ~ 2015/06/01	101	4	9	15	15.05	20	30
Stage 4	2015/06/01 ~ 2015/12/01	48	3	6	10	9.542	12	23
Stage 5	2015/12/01 ~ 2016/12/31	254	2	10	14	13.73	17	29

We can also classify these stocks by sectors which they belong to. In China, there are two stock exchanges: The Shanghai Stock Exchange (SSE) and The Shenzhen Stock Exchange (SZSE). Companies listed on SSE are usually state-owned enterprises (SOE) which play important roles in China's economy and have huge market capitalization, while companies listed on SZSE could be divided into two categories: mid-small cap companies and start-up companies. Table 4 summarizes the information of days of increasing streak for stocks in each sector.

Table 4

	Category	Number of Stocks	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
Sector 0	(SZSE) Mid-small Cap	121	1	7	10	10.71	14	27
Sector 1	(SSE) Large Cap	231	1	7	10	10.93	14	29
Sector 2	(SZSE) Start-Up	214	1	9	13	13.15	18	30

Also, we could classify these stocks by industry. Table 5 summarizes the information of days of increasing streak for stocks in each industry. What worth mentioning is that Bank Industry (S48) has significantly lower days of increasing streak than other industries.

Table 5

Industry Code	Industry Name	Number of Stocks	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
S11	Agriculture	8	1	6.50	9.50	10.12	14.25	20
S21	Mining	7	2	4.00	9.00	7.57	10.00	14
S22	Chemical	55	3	8.50	12.00	11.96	15.50	26
S23	Steel	1	14	14.00	14.00	14.00	14.00	14
S24	Nonferrous metals	9	1	7.00	11.00	10.56	13.00	20
S27	Electronic	42	4	9.25	13.00	13.64	18.00	30
S28	Automobile	24	1	5.75	9.00	8.75	12.00	18
S33	Household appliances	9	1	6.00	11.00	9.22	12.00	16
S34	Food and drink	16	1	5.00	9.00	8.69	11.00	20
S35	Textile and Apparel	15	1	5.50	7.00	8.53	11.00	23
S36	Light industry manufacturing	29	2	8.00	10.00	11.62	14.00	27
S37	Medical	49	1	7.00	10.00	11.51	15.00	26
S41	Utilities	11	5	8.00	10.00	10.18	11.50	16
S42	Transportation	11	2	7.00	11.00	11.64	16.50	23
S45	Commercial trade	7	8	9.00	12.00	11.86	14.50	16
S46	Leisure service	4	4	8.50	10.50	10.50	12.50	17
S48	Bank	8	2	4.00	6.50	6.13	8.00	10
S49	Non-bank finance	7	3	5.50	6.00	7.57	9.50	14
S61	Building materials	7	2	5.50	7.00	9.00	10.00	23
S62	Building decoration	33	3	7.00	11.00	11.27	15.00	20
S63	Electrical equipment	35	1	6.50	9.00	10.57	15.00	25
S64	Mechanic Equipment	87	1	9.00	12.00	12.84	17.00	29
S65	National Defense	4	13	18.25	20.50	19.75	22.00	25
S71	Computer	50	1	12.00	15.00	13.96	19.00	28
S72	Media	27	2	11.00	13.00	13.89	17.00	29
S73	Communication	11	7	9.50	16.00	14.55	19.00	20

To analyze what factors may significantly affect the length of the increasing streak, we collected the following indicators: Turnover Rate Reciprocal (TRR), Asset Per Share (APS), Success Rate (SR).

Turnover rate is the ratio of trading volume of the first trading day to total shares available for trading. And here, we take the reciprocal of turnover rate. Intuitively, a higher turnover rate, or a lower TRR, may indicate that the probability of a long increasing streak is slimmer. If the expectations of long increasing streak are strong, investors would hold their stocks and wait longer time to sell, rather than trading on the first day. So, there may be a positive relationship between TRR and days of increasing streak. Their relation is plotted in Figure 3.

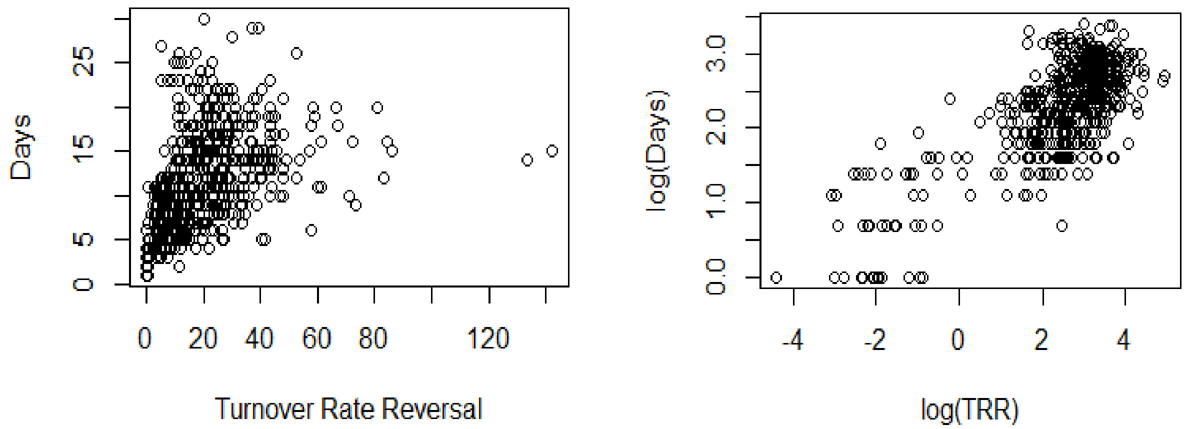

Figure 3

Asset per share may to some extend reflect the scale of capitalization of the company. The relation between APS and days of increasing streak is depicted in Figure 4.

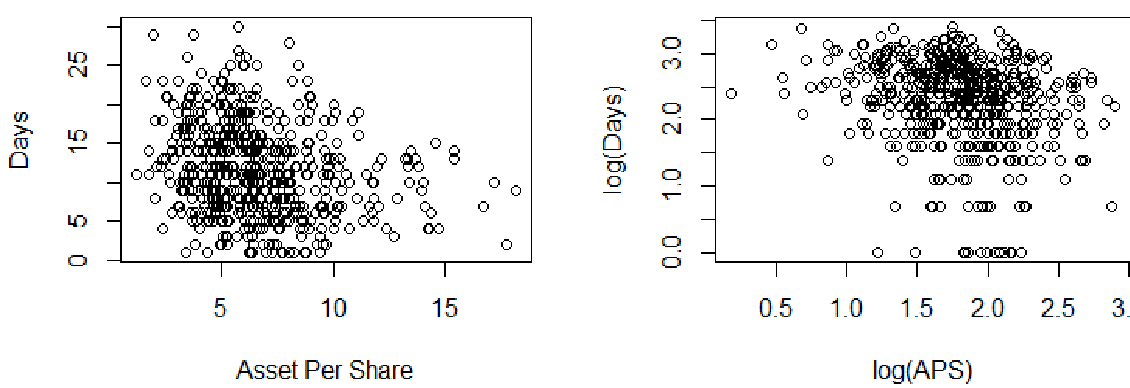

Figure 4

Success Rate is the ratio of the number of shares available to total IPO subscription. The lower the success rate, the more the stock is oversubscribed, and it is more difficult to subscribe successfully. So, there may be a negative relationship between SR and days of increasing streak. The relation between SR and days of increasing streak is depicted in Figure 5.

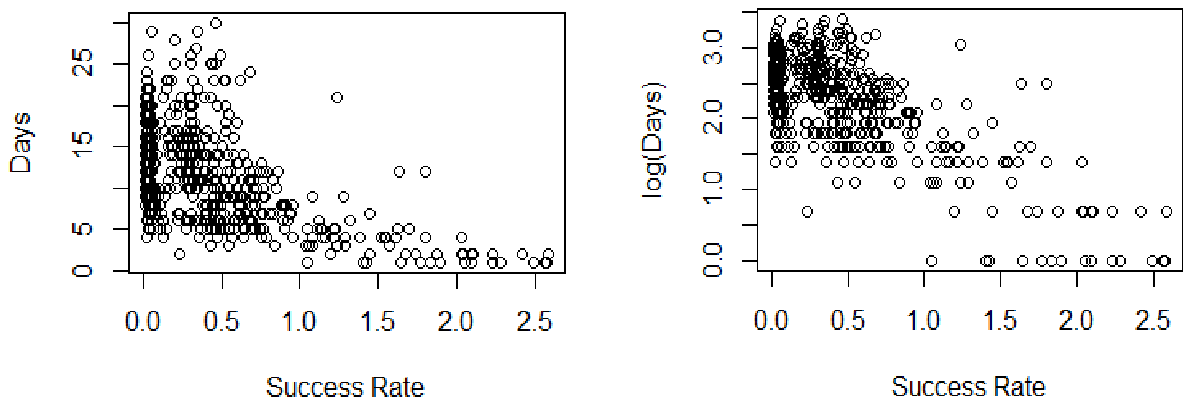

Figure 5

Models

We use two models to assist us in forecasting the day when the increasing streaks are going to break: A static model and a dynamic model.

The static model uses only the information available before the end of the first trading day. Here, we assume that the stock touches the 44% price limit on its first trading day, otherwise, as we mention before, there is no need to make any prediction since we have already known when the increasing streak breaks i.e. exact the first day.

The dynamic model uses all the information available prior to the end of the nth trading day to predict the probability that the increasing streak breaks on the n+1th trading day. In our dynamic model, we incorporate the estimated results obtained from the static model to represent all the static information, thus we can mainly focus on dynamic information which are not included in our static model.

It is worth mentioning here that we assume the information we obtain a few minutes prior to the end of a certain trading day is the same as what we can get after the end of that day. In practice, we may collect all the information, say, 3 minutes prior the end of trading on a certain day, inputting all the information to our model and using the output to make trading decisions immediately. If we postpone our trading decisions until the next trading day, we may be too late to use our output to avoid losses. Since there are always no significant changes in the last few minutes of trading within our concern, we simply assume there are no differences between these two situations.

Model One: Static Forecast

In our first model, static model, we use all the static information available before the end of the first trading day to predict how long the increasing streak is. The dependent variable is the days of increasing streak, while the independent variables are Turnover Rate Reciprocal (TRR), Asset Per Share (APS), Success Rate (SR), Stages, Sectors and Industries. Based on our observations of the relations between each independent variable and dependent variable, we take logarithm form for the dependent variable and some of the independent variables. After several trails of regressions with different combinations of independent variables, we exclude insignificant explanatory factors and incorporate only significant ones in this model.

Below is the static model:

$$\lg(Days) = \beta_0 + \beta_1 \lg(TRR) + \beta_2 \lg(APS) + \beta_3 SR + \beta_4 Stage1 + \beta_5 Stage3 + \beta_6 Stage4 + \beta_7 Sector1 + \beta_8 S48 + \varepsilon$$

where:

$Days$: the number of days that the increasing streak last.

TRR : the reciprocal of the turnover rate of the first trading day.

APS : asset per share.

SR : success rate, i.e. the ratio of the number of shares available to total IPO subscription.

$Stage1$: a dummy variable indicating whether the IPO date was from 2014-01-01 to 2014-06-01.

$Stage3$: a dummy variable indicating whether the IPO date was from 2015-03-01 to 2015-06-01.

$Stage4$: a dummy variable indicating whether the IPO date was from 2015-06-01 to 2015-12-01.

$Sector1$: a dummy variable indicating whether the stock is listed in SSE as a large cap company.

$S48$: is a dummy variable indicating whether the stock is a bank stock.

The regression results are shown in Table 6:

Table 6

Coefficients	Estimate (t value)
(Intercept)	2.76475***(26.866)
TRR	0.15754***(7.243)
APS	-0.30710***(-8.266)
SR	-0.48812***(-9.756)
Stage1	-0.34615**(-3.244)
Stage3	0.26978***(6.486)
Stage4	-0.28669***(-5.050)
Sector1	-0.22034***(-6.781)
S48	-0.54561***(-4.310)

R-squared	0.7213
Adjusted R-squared	0.7173
p-value	0.0000

***, ** indicate significance at the 99.9%, 99% level, respectively

We can see from this regression result that all the explanatory variables are significant at more than 99% confidence level, which indicates there are strong relationship between dependent and independent variables.

Model One: Results Analysis

Figure 6 shows the distribution of the prediction error of the model. The prediction error is defined as the difference between the forecasted days of increasing streak and the actual days of increasing streak.

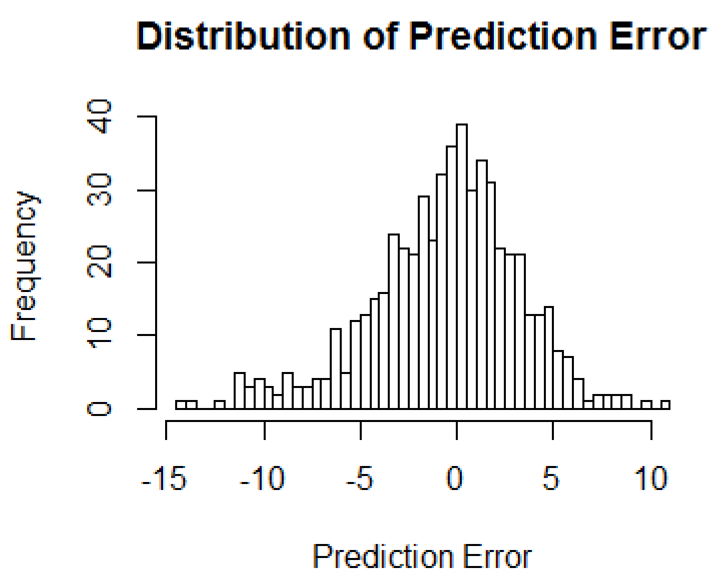

Figure 6

From Figure 6, we can see that the distribution of prediction error is left-skewed, which is consistent with the right-skewed distribution of days of increasing streak shown in Figure 1.

Table 7 shows the minimum, maximum, mean and quantile information of the prediction error.

Table 7

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
-14.4100	-2.8810	-0.2484	-0.5967	1.8690	10.7900

As we can see from Table 7, except few extreme cases, the prediction errors of this model are within acceptable range. The prediction by this model tends to be conservative, i.e. underestimating the actual days of increasing streak.

Model Two: Dynamic Forecast

In our second model, dynamic model, we use all the information available prior to the end of the t th trading day to predict the probability that the increasing streak breaks on the $t+1$ th trading day. This model is typically a probit model where the dependent variable is a dummy variable indicating the probability that the increasing streak breaks on the next trading day. Independent variables in this model are Time since IPO (T), Turnover Rate (TR), Turnover Rate Change (TRC), Small TRC (STRC), Large TRC (LTRC), Difference to Prediction (DP).

Turnover Rate Change is defined as: $TRC_t = \frac{TR_t}{TR_{t-1}}$. Intuitively, the larger the TR or TRC, the larger the possibility that the increasing streak breaks the next trading day.

Small TRC is defined as: $STRC_t = \begin{cases} 1\ if\ TRC_t < 1 \\ 0\ otherwise \end{cases}$

Large TRC is defined as: $LTRC_t = \begin{cases} 1\ if\ TRC_t > 7 \\ 0\ otherwise \end{cases}$

Intuitively, the possibility that increasing streak breaks is negatively related to Small TRC and positively related to Large TRC. The number “1” and “7” is chosen based on our observation. Other different but reasonable numbers will generate similar results.

In our dynamic model, we also incorporate the estimated results obtained from the static model to represent all the static information. So, Difference to Prediction here is defined as T minus prediction results from the static model, and it could be either negative or positive. It is worth mentioning that for a certain stock the prediction from the static model is the same while its T is increasing by 1 every trading day. So, as time goes by, for a normal stock, its Difference to Prediction will turn from negative to positive, becoming larger and larger. In this sense, DP is positively related to dependent variable.

Below is the dynamic model:

$$P = \beta_0 + \beta_1 T + \beta_2 TR + \beta_3 TRC + \beta_4 STRC + \beta_5 LTRC + \beta_6 DP + \varepsilon$$

where:

P : a dummy variable indication whether the increasing streak breaks on the next trading day.

T : the number of days since IPO.

TR : the turnover rate of current trading day.

TRC : the change of turnover rate compared to the last trading day.

$STRC$: a dummy variable indicating whether the change of turnover rate is small.

$LTRC$: a dummy variable indicating whether the change of turnover rate is large.

DP : the difference between the between prediction result to T .

The regression results are shown in Table 8:

Table 8

Coefficients	Estimate (t value)
(Intercept)	-1.02159***(-10.172)
T	-0.02711***(-3.483)
TR	0.02778***(13.570)
TRC	0.00201*(2.094)
STRC	-0.24481***(-3.606)
LTRC	0.45781***(4.690)
DP	0.12068***(12.068)

***, * indicate significance at the 99.9%, 95% level, respectively

Except the change of Turnover Rate (TRC) which is significant at 95% confidence level, all other variables are significant at more than 99.9% confidence level. And the results are also consistent with our intuiation.

Model Two: Results Analysis

To test the predictability of this model, we define Correctness as follows:

$$If\ \ P_t = 1:\ Correctness = \begin{cases} 1\ \ if\ \ \hat{P}_t > 0.5\ or\ (\hat{P}_t > 0.2 \text{ and } \dfrac{\hat{P}_t}{\hat{P}_{t-1}} > 2) \\ 0\ \ otherwise \end{cases}$$

$$If\ \ P_t = 0:\ Correctness = \begin{cases} 0\ \ if\ \ \hat{P}_t > 0.5\ or\ (\hat{P}_t > 0.2 \text{ and } \dfrac{\hat{P}_t}{\hat{P}_{t-1}} > 2) \\ 1\ \ otherwise \end{cases}$$

This definition basically says if the streak breaks next day, to be defined as “correct”, our predicted probability should be either larger than 0.5 or larger than 0.2 but twice the predicted probability of last day; if the streak doesn’t break next day, meeting the criteria above will give rise to be defined as “not correct”.

In this regression, each stock has as many observations as its days of increasing streak minus 1. The “1” here is due to the lag in independent variables. Thus, we have 6070 observations in total. Based on our definition of correctness, our model predicts 5608 observations correctly, a correctness rate of 92.3888%. This result means, given a specific day, we have that much confidence to predict correctly whether the increasing streak breaks on the next trading day.

However, predicting each observation correctly does not have too much economic meaning: what we truly care about is whether we can predict all the observations of a certain stock correctly. So, we define the New Correctness as follows:

For each stock i,

$$NewCorrectness_i = \begin{cases} 1 \;\; if \;\; Correctness_{it} = 1 \;\; for \; all \; t \\ 0 \;\; otherwise \end{cases},$$

where $Correctness_{it}$ is the t th observation of stock i.

Based on this new definition, the correctness slumped to 35.33%, which means, given a specific stock, we have 35.33% probability to predict correctly the exact day when its increasing streak breaks.

So, how significant this number is?

Based on 552 stocks (a very small number of stocks are removed due to lag in independent variables) that are taken into consideration, we define 3 types of prediction results by the corresponding trading action we take and summarize them in Table 9.

Table 9

Perfect Sell	Fail Sell (Buy-and-Hold)	Early Sell									
		1	2	3	4	5	6	7	10	12	14
195	238	63	23	10	3	8	3	5	1	2	1

The first type is Perfect Sell, which means in the cases of these 195 stocks, we accurately predict the day when the increasing streak breaks and take actions to sell those stocks accordingly. Perfect Sell avoids the problem of selling too early, and stops short of the plummets usually following the break, as well as possible soars, however, in some cases.

The second type is Fail Sell, which means in the cases of these 238 stocks, we fail to sell the stocks before the streak breaks. That means, in our prediction, we predict correctly in all the days since IPO expect the last day when the streak is going to break. In this case, we do not lose money by selling too early, which is the same as Perfect Sell. But we have to face the unknown risks, either gain or loss, in the upcoming future after the break of the streak. This is the typical Buy-and-Hold strategy we are going to use as a bench mark in our following discussions.

The third type is Early Sell, which means we sell our stocks too early before the increasing streak breaks. Definitely, to various degrees, we lose our chances to gain what we “should” earn.

However, the same as it is in Perfect Sell, we give up risking more in the unknown period after the streak breaks.

Figure 7 depicts the distribution of prediction error (days), which corresponds to "Fail Sell" and "Early Sell" in Table 9. It is worth mentioning that even though the error for those 238 stocks are 0, it does not mean they are sold exact on the streak-broken day. Instead, due to the prediction mistake on that day, those stocks fail to be sold. So, the "error" here could be regarded as the difference between the streak-broken day and the first day we have a mistake in our prediction. (0 also indicates a wrong prediction.) From Figure 7, we can also see that there are 63 stocks that are sold one day before the break of the streak, and only 1 stock that are sold 14 days earlier.

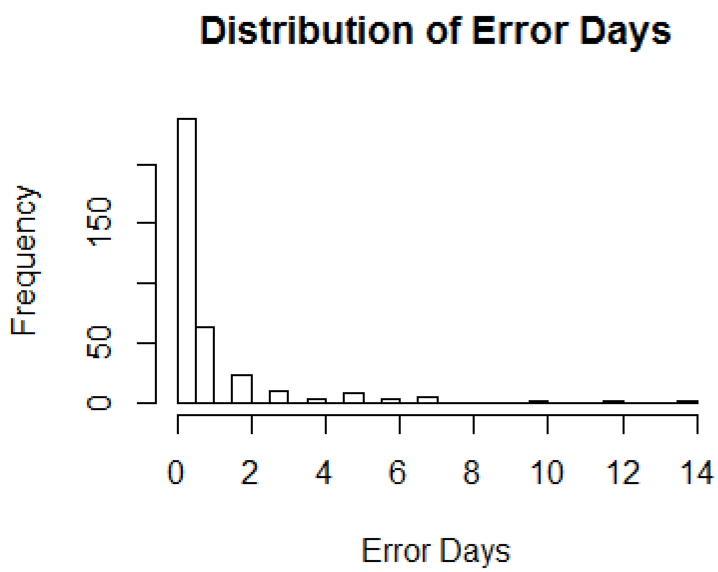

Figure 7

Next, we compare our trading actions based on our prediction results to Buy-and-Hold strategy. Our relative performance compared to Buy-and-Hold could be expressed by the expectation of relative gain or loss given the holding period return of Buy-and-Hold strategy. The holding period begins on the streak-broken day, and ends based on investors' definition.

The formula is like this:

$$\begin{aligned} E(Gain) &= (0 - E(HPR))P_{PS} + (E(HPR) - E(HPR))P_{FS} + (E(ES) - E(HPS))P_{ES} \\ &= -E(HPR)P_{PS} + (E(ES) - E(HPS))P_{ES} \end{aligned}$$

where:

HPR : holding period return of Buy-and-Hold strategy.

ES : the opportunity loss of early sell, always negative.

P_{PS} : probability of Perfect Sell.

P_{FS} : probability of Fail Sell, i.e. Buy-and-Hold.

P_{ES} : probability of Early Sell.

To be specific, based on our dataset,

$$P_{PS} = \frac{195}{552} = 0.3533$$

$$P_{FS} = \frac{238}{552} = 0.4312$$

$$P_{ES} = P(ErrorDays = 1) + ... + \mathrm{P}(ErrorDays = 14) = \frac{63}{552} + ... + \frac{1}{552} = 0.2156$$

$$E(ES) = -\frac{P(ErrorDays = 1)}{P(ES)} * (1.10^{1} - 1) + ... + \frac{P(ErrorDays = 14)}{P(ES)} * (1.10^{14} - 1) = -0.3062$$

From the result of $E(ES)$, we can see that when the holding period return of Buy-and-Hold is assumed to be 0, our strategy occurs a relative loss of $E(ES) * P_{ES} = -0.0660$ compared to Buy-and-Hold.

In fact, there is a linear relationship between expected gain or loss and holding period return:

$$E(Gain) = -E(HPR)(P_{PS} + P_{ES}) + E(ES)P_{ES} = -0.5688 * E(HPR) - 0.0660$$

With various given expected HPR, we could get different expected values of relative gain or loss, as shown in Table 10.

Table 10

HPR	Relative Gain	HPR	Relative Gain	HPR	Relative Gain
-50.00%	21.84%	-15.00%	1.93%	20.00%	-17.98%
-45.00%	19.00%	-10.00%	-0.91%	25.00%	-20.82%
-40.00%	16.15%	-5.00%	-3.76%	30.00%	-23.67%
-35.00%	13.31%	0.00%	-6.60%	35.00%	-26.51%
-30.00%	10.46%	5.00%	-9.45%	40.00%	-29.36%
-25.00%	7.62%	10.00%	-12.29%	45.00%	-32.20%
-20.00%	4.77%	15.00%	-15.13%	50.00%	-35.04%

From Table 10, it is easy to see that the profitability of our model is largely depends on the HPR of Buy-and-Hold strategy. When HPR is negative, and lower than the threshold -11.60%, our strategy could outperform Buy-and-Hold. However, when HPR is larger than the threshold, our strategy will be less effective than simply Buy-and-Hold, due to the “conservativism” of this model.

Conclusion

"Hit new stock" is an interesting and exciting phenomenon in China's stock market. To assist investors in making wise decision, we conduct our research by applying two models, static model and dynamic model, into China's IPO stock market from the beginning of 2014 to the end of 2016. From the empirical evidence given by the static model, factors such as Turnover Rate, Asset Per Share, Success Rate in purchasing, etc. have significant influences on the length of the increasing streak after IPO. We also find that sectors, market stages, as well as industries may also play significant roles in deciding how long could this streak last. Then we incorporate our results from the static model into the dynamic model, and forecast the probability that the streak breaks on the next trading day. Finally, we compare our prediction-based trading strategy with simple Buy-and-Hold strategy, and get different expected gain or loss levels in different market scenarios.

However, due to the limited time, resources and techniques, our work is far from perfect. Future works could also be done in the following aspects:

First, incorporate more explanatory variables into the regression model. In our study, we mainly focus on quantitative factors that could be comparatively easily obtained in the market. However, we pay few attention to factors that are difficult to be quantified, such as relations among IPO company, government, investment banks, and investors. Also, future study could try to use more effective indicators to describe emotions in the market, for example, include intraday market information, etc.

Second, try more forms of dependent and independent variables. In our models, we try dummy variables, logarithm forms, and 1-lag terms on variables. Future study could try more forms, such as quadratic forms, more lag terms as well as combinations of independent variables.

Third, develop more effective trading strategies. In our paper, we simply compare our prediction results with Buy-and-Hold strategy. More effective strategies and more convincing comparisons could be made by trying to apply the results of the prediction model into different ways.

Last but not least, apply these models into newly-generated market data. We can use new market data to test whether the conclusion we get from this study still hold in the long run, so as to test the robust of these models, and if possible, apply the models into real trading.

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