Momentum Trading, Contrarian Trading, and Firm Age

Robert Palmarozza

Abstract

This paper tests whether firm age is an important determinant of momentum and contrarian trading behavior. Because less is known about the interaction between expected future economic conditions and firm profitability for young firms, investors are more likely to use naïve extrapolations at past performance to project future performances. While we find only weak evidence of momentum trading, we find significant evidence of contrarian trading. In general, stock prices for firms with more recent IPO dates (i.e., young firms) show significantly more contrarian trading than firms with less recent IPO dates.

Introduction

In 1863, Jules Regnault first hypothesized that markets were informationally efficient. For Regnault, informational efficiency implied that all available information on an asset is already incorporated in the asset's price and that any new information is rapidly incorporated in asset prices. Because asset prices include all new information, future changes in stock prices should follow a random walk and historical prices should not affect future prices. Over time, this claim that markets are informationally efficient (i.e. the efficient market hypothesis) has gained both critics and supporters. Some of the more influential critics have been behavioral economists who study the effect of psychological, social and emotional factors in asset pricing. Behavioral economics rejects the idea that stock prices follow a random walk and argues that historical prices play an important role in determining future prices. If historical prices determine future prices both contrarian and momentum trading may occur. A contrarian trade assumes that an asset that has performed well in the past is more likely to exhibit lower average returns in the future. Momentum traders by contrast, assume that assets that have historically performed well are more likely to perform well in the future.

If traders use historical prices in this way, investors will tend to overreact to information causing a clear link between past and future prices. Although investors incorporate relevant information into an asset price, certain information may be considered more important in an investor's mind. Most important, historic prices can serve as in indicator of asset strength. One possible rationale for this is investor herding, which implies that investors will use other investors as an indicator of future market prices. When investors herd, they react to the reaction of other investors. Therefore, an increase in prices, leads others to buy based on the fact of higher value.

Confirmation bias may produce a similar effect. If investors exhibit confirmation bias, high current prices confirm assumptions on future asset returns and lead to more buying

Previous studies of stock momentum have examined momentum across different countries as well as by sector size, market cap and a series of other factors in (Liew and Vassalou 2000 and Venkataramani 2003) . The results show that different portfolios and different sectors exhibit degrees of stock momentum. For example, Liew and Vassalou (2000) show evidence of stock momentum in eight of ten developed countries. They explain that these differences are the result of asymmetric dispersion and utilization of information in different markets. These differences in information may be the key to stock momentum and in areas where information is less prevalent or more difficult to assemble; momentum may be higher as investors rely on more biases.

This paper seeks to further examine information dispersion, stock momentum, and contrarian trading behavior by dividing assets into a series of portfolios sorted by IPO date and then testing for momentum and contrarian trading in the top and bottom decile of each of the portfolios. We expect that IPO date momentum and contrarian trading behavior because private companies face less demanding requirements for information releases than public companies and it may take the market some time after an IPO to determine the actual value of the asset. Also, when investors have less knowledge of the link between expected future conditions and firm profits they are more likely to herd or use naïve extrapolations of past performance predict future stock prices. Because investors know less about link between expected future conditions and firm profits for firms with more recent IPO dates, stock prices for firms with more recent IPO dates should show more momentum and contrarian trading behavior. Using this data set we will also study the profitability of momentum and contrarian trading strategies.

Literature Review

In the first important study of stock momentum, Jegadeesh and Titman (1993) examined stock momentum in a portfolio structure by sorting stocks into categories of winners and losers. They then examine the returns for the winners and losers in later periods. For the purpose of their study, winners were stocks in the top decile of their sample, with losers were in the bottom decile. Jegadeesh and Titman analyze mid-range returns using over 3-12 months using 16 different strategies. Specifically, they considered historical returns over the previous 1-4 quarters and considered holding periods of 1-4 quarters after. They find substantial evidence of momentum. For instance, stocks in the top decile over a 6-month period showed excess returns of 12.01% over the subsequent 6 months period. Such outcomes are difficult to reconcile with the efficient market hypothesis. One might be tempted to dismiss the results as a fluke. However Jegadeesh and Titman (2001) find similar results using a later time frame.

The abnormal return structure noted by Jegadeesh and Titman encouraged others to examine the causes of stock momentum (Venkataramani 2003, Hong and Stein 1997, Shaw and Womack 1999, Park and Sabourian 2001, and Sapp and Tiwari 2004). Venkataramani (2003) tests whether stock momentum varies by stock exchange listing, firm size, and sector. Over the time period of 1962 to 2001, Venkataramani finds evidence of stock momentum in all sectors except for utilities. He also found evidence that stock momentum was lower for smaller firms. Similar to Venkataramani's paper, Moskowitz and Grinblatt (1999) examined the prevalence of momentum effects across industries. The authors identified industry momentum as the source of most of the momentum trading profits at the 6-12 month horizon. After adding controls for size, book to market and individual stock momentum, industry portfolios exhibit significant momentum. Based on these results, they hypothesized those current views of the industry influence future prices. When investors perceive industries as hot, they forecast higher returns in future periods. This leads to overconfidence in hot industries that in turn leads to mispricing.

Other types of information problems may also cause momentum in stock prices. For instance, Sapp and Tiawari (2004) argue that herd behavior may cause momentum. Herd behavior occurs because some investors are considered “smart money” investors by less knowledgeable investors. These less knowledgeable investors then simply follow the actions of the smart money investors because less knowledgeable investors perceive that smart money has a better understanding of financial markets. This allows investors to benefit from shared market strategy in the short run as those that bought past winners are benefiting from those that also purchased past winners. The brief change in asset price is only temporary as the market eventually adjusts to reach a price that reflects fundamentals. However, for certain durations, following smart money can be a successful strategy. Park and Sabourian (2004) also examined herding and contrarian behavior in informationally efficient markets. They point out that if markets were efficient, investor herding should not exist in any way that could cause market price to differ from the fundamental value. However, investor’s strategies become similar to each other causing market returns that would not exist otherwise. This social learning could alter the price of an asset and cause more variation in prices.

To examine how markets react to the dispersion of information, Hong and Stein (1997) postulate that traders can either by considered “news watchers” or “momentum traders.” If information is slowly released to the public, then the price of an asset should reflect that flow of information. However, this also creates opportunity to exploit trends in the market if a trader catches onto the information early enough. For simplicity, Hong and Stein assume that both news watchers and momentum traders have bounded rationality, meaning that investors use all available information, but only when it pertains to their trading ideology. Essentially, news watchers rely on information about future fundamentals, while momentum traders rely on past information to determine future asset trend prices. The results show that successful trading strategies can be exploited in the short to mid run, if an investor can catch a stock on an upswing or downswing. This exploitation of the market though leads to a mismatch of the fundamental asset value and the current market price.

Such mispricing problems extend to markets for IPOs; a series of papers including Krigman, Shaw and Womack (1999), Aggrawal and Rivoli (1990), and Clark (2002) document that assets prices have a tendency to fluctuate wildly post IPO. Krigman, Shaw and Womack (1999) investigate the ill-fated attempts of underwriters to effectively value IPOs. They are able to show that first date returns are able to predict future performance. To show this, they divide IPOs into two separate categories, hot and cold IPOs. IPOs are divided based on first day flipping activity, an asset that is constantly flipped is considered hot. The authors found that cold IPOs continue to underperform and hot IPOs continue to do well in the following year. The possible explanation for this relies in underwriter's willingness to let original shareholders win at the expense of new investors. This causes the market to correct itself in the first few days following the release of new information.

Aggrawai and Rivoli (1990) note two possible explanations for abnormal returns to IPOs. First, systematic underpricing during an IPO or a mismatch between the price and the fundamental value in the early aftermath of trading could cause these returns. Second, the lack of transparency for some firms may make it difficult for investors to forecast profits. When profit forecasting is difficult, past prices attain greater influence in profit projections. This led Clark (2002) to hypothesize that the age of a firm may have some relationship with the returns post IPO. A statistically significant positive relationship exists. Thus, informational efficiency may be harder with younger firms as the quality and quantity of information is lower. This idea is consistent with stock momentum theories that contend that either information is being correctly utilized or information may not exist in enough quantity causing biases to become more prevalent.

The literature on IPO mispricing may therefore offer insights into stock momentum. Both events occur where markets may not disperse the full information currently available. Both events also seem to be triggered by investor biases about assets as in the case of hot and cold IPOs and industries. Stock momentum and IPO mispricing both focuses around investors hoping to exploit trends in the market using sometimes less than reliable information and in conjunction may be able to tell a bigger story about how investors truly make decisions on which assets to invest in. The profitability of momentum trading diminished in recent years, however as Jegadeesh 2001 proved, stock momentum is still prevalent to a lesser extent in period's pre 2001.

Data

To examine the relation between firm IPO date (i.e. firm age) and stock momentum, I assembled data using the equity screen on a standard Bloomberg terminal. I used United States stocks with a listed initial public offer (IPO) date before January 1st, 2001. In previous studies, the

United States has shown high degrees of stock momentum and vast literature on specifically American markets allows for the most comparative material. While the Bloomberg system does not list all IPO dates for all U.S. stock, the initial screen yielded over 1,900 results.

Following Jegadeesh, the selection of dates 3 months, 6 months, 9 months and 12 months into the future followed the selection of the random date. A custom Microsoft Excel sub-routine shown in Figure 6 generated a randomly selected a non-holiday weekday. The program searched for a random date and used Microsoft Excel's built-in weekday function to determine if the randomly selected day was a weekday. The Excel weekday function provides an integer value of 1-7 for each day of the week based on the users requested starting point. The sub-routine specifications searched for a random date between 1/1/2002 and 1/1/2009 as the study ranged from 2001-2010 and data required looking 1 year into the past or future.

Due to holidays, weekends, and system restrictions, I used random dates within one week of the initial end date as the actual end date. The interval of one week follows other momentum studies which have used lag periods of one week to determine stock momentum (Jegadeesh 2001). We removed assets only if we could not generate sufficient data from the one-week grace period. We lost about 10% of data points because of such failures. We also classified assets using the Industry Classification Benchmark (ICB).[1] The ICB classification breakdown includes the following industries: 1) health care; 2) technology; 3) financial services; 4) industrials; 5) consumer services; 6) consumer goods; 7) oil and gas; 8) basic materials; 9) utilities; and 10) telecommunications. We didn't examine utilities because Venkataramani (2003) found evidence

[1] The ICB was launched by Dow Jones and FTSE in 2005 as a way to classify companies on 4 levels

of momentum in each industry except for utilities. We also dropped telecommunications stocks because the sample size was too small (<20).

A breakdown of IPO by industry, using the ICB classification, and information about each industry can be found in Table 1.[2] The graph in Figure 1 also shows the breakdown of IPO dates by industry. Industries like basic materials have an average IPO year of 1976 while technology has an average IPO year of 1992. Industry stagnation, with lack of new competitors, could contribute to lower (less recent) average IPO dates. The final results include over 1600 assets classified using ICB codes. Using this data, I constructed five portfolios consisting for the following IPO date ranges: 1) (2000, 1995); 2) (1995, 1990); 3) (1990, 1985); 4) (1985, 1980); 5) (1980,). Thus, the trading period of (2000, 1995) includes every stock in the portfolio with an IPO date before 1/1/2001 and after 1/1/1996. The portfolios range in size from 100-500 stocks. Table 2 reports the average IPO date by industry.

<u>Trading Strategies</u>

Following trading strategies employed in Jegadeesh and Titman (1993) and Moskowitz and Grinblatt (1999) we calculate returns over 1 to 4 quarters with holding strategies of 1 to 4 quarters. Earlier results showed significant momentum up to 7 months after: after 7-month period contrarian produce higher results than momentum strategies. Because earlier results show very little to no stock momentum in any trading periods greater than 7 months, we reduced trading strategies to : 1) 3 Before / 6 After; 2) 6 Before / 6 After; 3) 3 Before / 3 After; 4) 9 Before / 3 After. For instance, the 3 before / 6 after strategy uses the net change percentage over the 3 months

[2] Bloomberg system limitations stopped accurate classification of industries by their Standard Industry Classification (SIC) code. SIC codes are seen in Venkataramani's and Moskowitz and Grinblatt's (1999) papers.

leading up to the cutoff date and the subsequent excess returns for the period 6 months after the cutoff date. These net changes represent the excess returns for each asset over a given period. We calculated excess returns by subtracting the difference of an assets performance from the total market CRSP. (Jegadeesh 1993). Based on pre-period returns, we grouped assets into top and bottom deciles (i.e., winners and losers). Decile portfolios ranged from approximately 10 to 50 assets because of differences in portfolio sample size. The average post return calculated for each decile portfolio leading to the results is shown in Table 4.

Results

Table 3 shows the excess returns by trading strategy, IPO date. We calculate average by month excess returns for each trading strategy by dividing total returns by the number of post period's months or J. The *1995-2000/WINNERS/3 before 3 After* result of .02 means that an asset ranked in the top decile of the last 3 month return results was expected to show excess returns of 2% per month in the subsequent 3 months. The smallest average excess return (-8.6%) occurred for *1995-2000/WINNERS/9 before/3 after* while the largest excess return (25.2%) occurred for *<1980/LOSERS/ 9 before/3 after*. Figures 2 and 3 display the Table 3 data separately for winners and losers.

The winner data reported in Figure 2 shows higher excess returns for later IPO dates. While excess returns for winners did not show large deviation from zero, longer pre-period trading strategies show lower excess returns. The winner trading strategies with pre-periods of 6 and 9 months show negative returns. In contrast, winner trading strategies that examine pre-periods of 3 months generally exhibit positive excess returns. *3 Before/ 3 After* shows positive excess returns for every IPO date. This is the only evidence of momentum in the study. Trading strategies that examine data from longer pre-periods shows less momentum. We can see these results in Figure 3. Figure 3 shows excess returns on the vertical axis. While there is no clear trend, trading strategies with longer pre-periods are far more likely to show negative returns. Variation in the number of months in the post period has no impact on returns.

The loser data displayed in Figure 3 shows a contrasting trend for losers. While the trading strategies with longer pre-periods showed lower excess returns in winners, longer pre-period trading strategies (6 and 9 months before) show higher excess returns in losers. Exceedingly high returns are seen in *9 Before / 3 After*, with excess returns over 9% for each IPO date range. Regardless of IPO date, loser portfolios exhibit positive excess returns in each trading strategy. Only 3 of the 40 trading strategies exhibit excess returns less than 5%. Finally, there is no clear trend in excess returns for variations in the duration of post-period trading strategies.

To test the significance of the results in Table 3, we regress excess returns on trading strategy, IPO date range and winners. IPO Date is indicated with 1, 2, 3, 4, and 5 (where 5 = 1995-2000), and we code winners and losers with a dummy variable (0: Losers, 1: Winners). I decompose trading strategy into two variables: the number of pre-period (before) months and the number of post-period months (after). Because contrarian (momentum) trading will generate negative (positive) excess returns for winners and positive (negative) excess returns for losers, we create interaction variables for winners/loser and IPO date as well as winners/loser and the length of the pre-period. Tables 4 and 5 show the regression results. Table 4 shows that the variables before, winners_before, IPO date, and winners_IPO date are all significant at the 6% level with p values of .032, .058, .000, .032 respectively. After, the only non-significant variable, measures number of months measured after a cutoff date. Table 5 adds an interaction - winners_after to check whether excess returns for winners and losers respond differently to variations in the post-period months. The results showed no significance for the interaction variable and did not change the results overall.

IPO date's coefficient of .024 indicates that for loser stocks an increase in the date rage of one unit is associated with a 2.4 percentage point increase in excess return. This result supports the initial hypothesis of more contrarian trading for stocks with more recent IPO dates. We suspect that these higher returns in newer portfolios result from less available information. The interaction of winners_IPO date shows lower expected excess returns in winners. Winners_IPO date's coefficient of -.012 indicates that for winner stocks an increase in the date rage of one month is associated with a 1.2 percentage point decrease in excess return. Thus, both results support the contrarian behavior found in Table 3. Before's coefficient estimate of .006 indicates that for every one month increase in the number of pre-period months, excess returns increase by .6 percentage points for losers. Winner_before's coefficient estimate of -.006 indicates that for every one month increase in the number of pre-period months, excess returns decrease by .6 percentage points for winners.

Conclusion

Overall the results of this paper do not directly coincide with previous stock momentum studies. The results show positive excess returns in the bottom decile (losers) indicating that contrarian trading, not momentum trading, is present. However, more recent papers show lower levels of momentum. For instance, Jagadeesh and Titman (1993) reports much higher levels of momentum than Jegadeesh and Titman (2001) and Moskowitz and Grinblatt (1999). The only evidence of stock momentum in the present student is found in strategies with short pre and post periods (*3 Before / 3 After* and in some cases in a *3 Before / 6 After*). But these trading strategies do not show excess returns greater than 4%. We did find strong evidence contrarian trading strategies. Moreover, the evidence of contrarian trading is stronger for longer pre-periods and stocks with more recent IPO dates. This evidence may show the markets ability to identify stocks that deviated too far from their fundamental price. As technology increases, trading strategies may have deviated farther from the attitudes that caused momentum pre 1990. Future research is needed to determine how assets in loser portfolios performed after the post-period months.

While we found little evidence to support our initial hypothesis that stocks with more recent IPO dates would exhibit higher levels of momentum and instead found that stocks with more recent IPO dates exhibit higher levels of contrarian trading, further research is required to determine if this is indicative of a possible change in market sentiment. To better understand the causes of the link between IPO dates and contrarian trading, subsequent research should increase the number of stocks in the sample and add controls for both IPO date and industry/sector. Such an analysis would allow us to test whether industries exhibited different levels of momentum depending on IPO.

Bibliography

Agarwal, Sumit, Liu Chunlin and S. Ghon Rhee. 1990. Investor demand for IPOs and aftermarket performance: Evidence from the Hong Kong stock market, *Journal of International Financial Markets, Institutions, and Money* 18, 176-190

Clark, David T. 2002. A study of the relationship between firm age-at-IPO and aftermarket stock performance. *Financial Markets, Institutions & Instruments* 11, 385-400.

Hong, Harrison and Jeremy C. Stein. 1997. A Unified Theory of Underreaction, Momentum Trading and Overreaction in Asset Markets. National Bureau of Economic Research, 6234.

Jegadeesh, Narasimhan and Sheridan Titman. 1993. Returns to buying winners and selling losers: Implications for stock market efficiency. *The Journal of Finance* 48, 65-91.

Jegadeesh, Narasimhan and Sheridan Titman. 2001. Profitability of momentum strategies: an evaluation of alternative explanations. *The Journal of Finance* 56, 699-720.

Krigman, L., W. H. Shaw, and K. L. Womack. 1999. The persistence of IPO mispricing and the predictive power of flipping. *The Journal of Finance* 54, 1015–1044.

Moskowitz, T. J. and M. Grinblatt. 1999. Do industries explain momentum? *The Journal of Finance* 54, 1249–1290.

Park, Andreas and Hamid Sabourian. 2001. Herding and contrarian behavior in financial markets. *Econometrica* 79, 973-1026.

Sapp, Travis and Ashish Tiwari. 2004. Does stock return momentum explain the "smart money" effect? *The Journal of Finance* 59, 2605-2622.

Venkataramani, Chandramouliswaran, 2003. Random walk hypotheses and profitability of momentum based trading rules, Ph.D. Dissertation, University of Pennsylvania.

Figures and Tables

Table 1

OBSERVATIONS BY IPO DATE AND SECTOR

	Health Care	Technology	Financials	Industrials	Consumer Services	Consumer Goods	Oil & Gas	Basic Materials
1995-2000	93	176	88	90	72	37	20	11
1990-1995	75	85	132	100	82	38	22	8
1985-1990	18	27	53	27	13	22	10	8
1980-1985	17	22	18	19	18	6	6	0
<1980	27	23	32	53	28	32	20	24
Total	230	333	323	289	213	135	78	51

Table 2

AVERAGE IPO DATE BY INDUSTRY

Industry	Min Year	Max Year	Average
Health Care	1929	2000	1990.7087
Technology	1915	2000	1992.8108
Financials	1948	2000	1990.5356
Industrials	1908	2000	1987.0311
Consumer Services	1928	2000	1989.5117
Consumer Goods	1919	2000	1983.6741
Oil & Gas	1920	2000	1983.7821
Basic Materials	1915	1999	1976.0588

Table 3

AVERAGE POST PERIOD RETURN FOR BOTH WINNERS AND LOSERS BY IPO DATE

		3 BEFORE 3 AFTER		6 BEFORE 6 AFTER	
		WINNERS	LOSERS	WINNERS	LOSERS
1995-2000	Average	0.020797237	0.060491963	-0.082014252	0.083297766
1990-1995	Average	0.003928358	0.082862763	-0.073291899	0.097558322
1985-1990	Average	0.036662286	0.050877704	-0.033606665	0.092061989
1980-1985	Average	0.033522278	0.066720171	-0.023414389	0.0817389
<1980	Average	0.013161365	0.036523323	0.009659769	0.101541846

		3 BEFORE 6 AFTER		9 BEFORE 3 AFTER	
		WINNERS	LOSERS	WINNERS	LOSERS
1995-2000	Average	-0.044350176	0.038538221	-0.086415395	0.149431721
1990-1995	Average	-0.039344393	0.068169077	-0.043296842	0.143524993
1985-1990	Average	0.002092879	0.080852554	-0.01747292	0.089169671
1980-1985	Average	0.017272403	0.054346862	-0.035992746	0.131753968
<1980	Average	-0.008544621	0.074688492	-0.015949024	0.25287529

Table 4

REGRESSION RESULT OF POST PERIOD EXCESS RETURNS AGAINST MONTHS BEFORE, MONTHS AFTER, IPO DATE, WINNER/LOSER, (Interaction Variables WINNERS_BEFORE, WINNERS_IPODATE)

Linear regression .

```
Linear regression                                      Number of obs =      40
                                                       F(  6,    33) =    9.44
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.7401
                                                       Root MSE      =  .02228
```

postreturn	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
before	.0063756	.0028407	2.24	0.032	.0005962	.012155
winners_before	-.0065973	.0033537	-1.97	0.058	-.0134205	.0002259
after	-.0017399	.0021568	-0.81	0.426	-.0061279	.0026481
ipodate	.0245997	.0048457	5.08	0.000	.0147409	.0344584
winners	.0389931	.0263038	1.48	0.148	-.0145224	.0925087
winners_ipodate	-.0122937	.0054852	-2.24	0.032	-.0234534	-.001134
_cons	-.0461674	.0216952	-2.13	0.041	-.0903066	-.0020282

Table 5

REGRESSION RESULT OF POST PERIOD EXCESS RETURNS AGAINST MONTHS BEFORE, MONTHS AFTER, IPO DATE, WINNER/LOSER, (Interaction Variables WINNERS_BEFORE, WINNERS_IPODATE)

INCLUDING INTERACTION OF WINNERS_AFTER

.

```
Linear regression                                      Number of obs =      40
                                                       F(  7,    32) =    8.79
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.7435
                                                       Root MSE      =  .02247
```

postreturn	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
before	.006081	.0028063	2.17	0.038	.0003648	.0117972
top_before	-.0060081	.0032438	-1.85	0.073	-.0126155	.0005993
after	-.0033603	.0036454	-0.92	0.364	-.0107857	.004065
ipodate	.0245997	.0047805	5.15	0.000	.0148622	.0343371
top	.0213154	.02845	0.75	0.459	-.0366354	.0792662
top_ipodate	-.0122937	.0054345	-2.26	0.031	-.0233635	-.0012239
top_after	.0032409	.0043304	0.75	0.460	-.0055798	.0120617
_cons	-.0373285	.0219397	-1.70	0.099	-.0820184	.0073613

Figure 1

GRAPH OF INDUSTRY BREAKDOWN BY IPO PERIOD

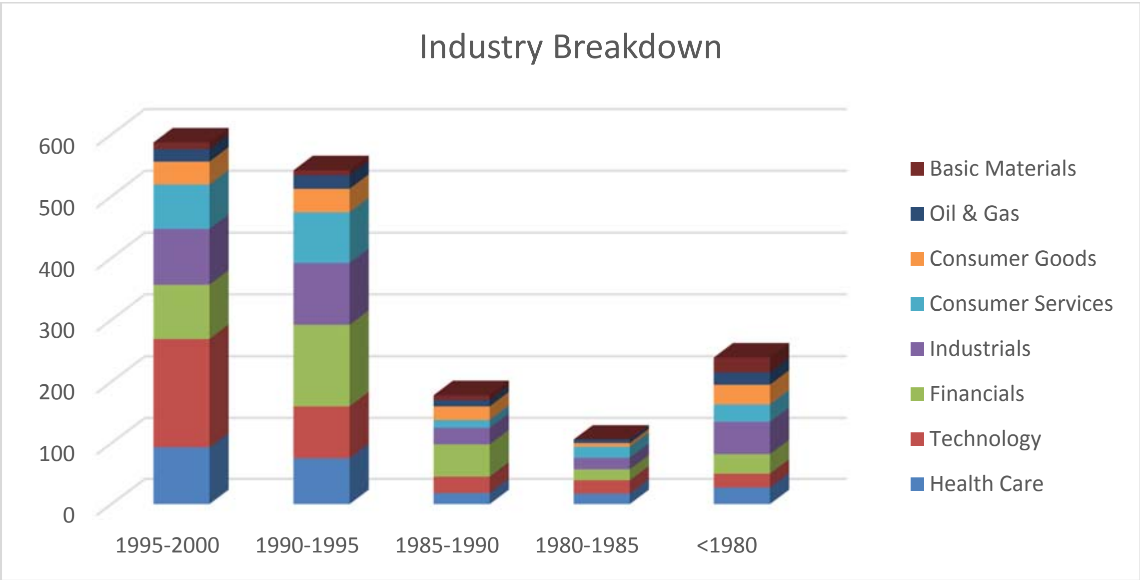

Figure 2

RETURNS FOR WINNERS BY IPO DATE

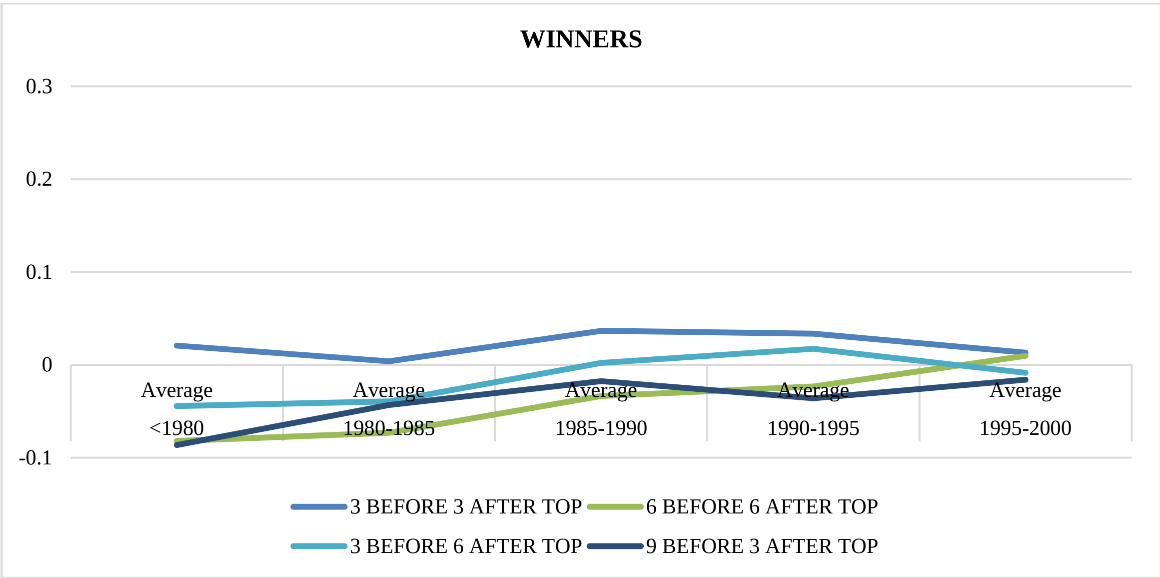

Figure 3

RETURNS FOR LOSERS BY IPO DATE

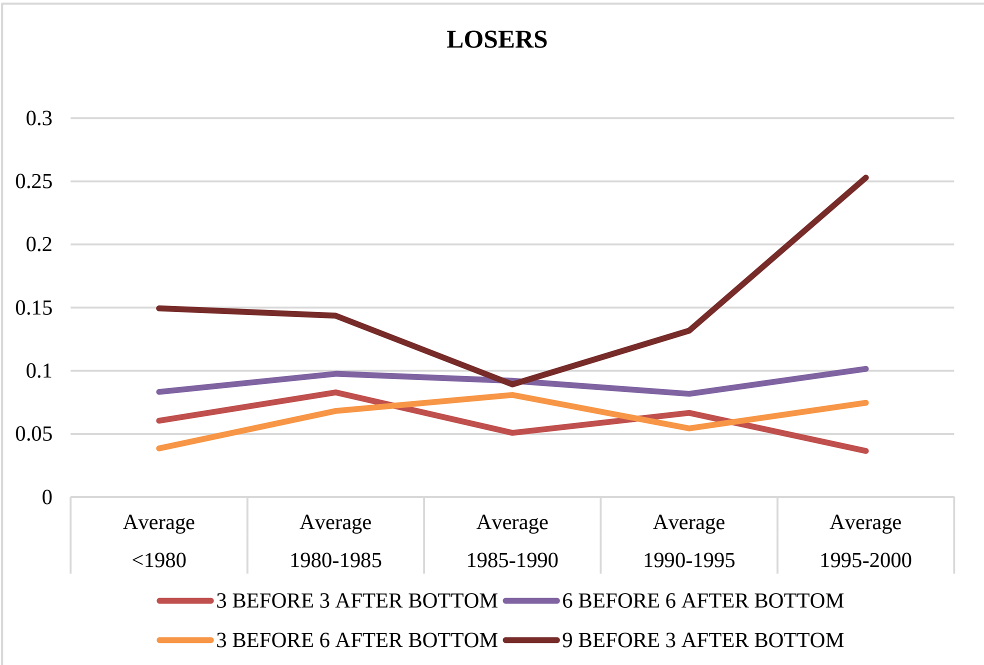

Figure 4

EXCEL FUNCTION TO GENERATE RANDOM DATE

```
Sub Random WorkDay()
   Dim ws As Worksheet
   Dim x As Integer, Temp As Date, Beg As Date

   x = 2
   Beg = "1/1/2002"

   While (Cells(x, 1).Value <> "")
         Temp = WorksheetFunction.WorkDay(WorksheetFunction.RandBetween(Beg - 1,
         WorksheetFunction.EoMonth(Beg, 105) - 1), 1)

      While (WorksheetFunction.Weekday(Temp, 1) < 2 Or WorksheetFunction.Weekday(Temp, 1) > 6)
          Temp = WorksheetFunction.WorkDay(WorksheetFunction.RandBetween(Beg - 1,
         WorksheetFunction.EoMonth(Beg, 120) - 1), 1)
      Wend

      Cells(x, 7) = Temp
      x = x + 1
   Wend

End Sub
```