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NEW HIGHS AND PERCENTAGE RETURN

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Abstract

We will in this paper investigate the empirical relationship between the number of new highs (lows) and percentage return for 2500 stocks. The theoretical argument is that stocks that historically have produced large long (short) returns all have in common that they systematically made new highs (lows). We find that the number of highs (lows) is statistically significant and can together explain up to 35% of the variation of stock return.

Keywords: trend following, new highs, investment

Introduction

Many different authors such as Markowitz (1959), Sharpe (1964), Covel (2004), Pedersen and Zwart (2004) and Gwilym et al (2010) have described the benefit of using trend-following models when making investments in financial markets. A trend can be defined in many different ways. One way to define it is by using risk adjusted returns. The higher the risk adjusted return is the more the asset is trending. Another way is to look at price increase and price drawdown. The higher the percentage increase is and the lower the price drawdown is the more the asset is trending. A third way is to calculate the number of new highs (lows) a stock has made. The higher such a number is the more the asset is trending. The interesting thing to note is that all assets that historically have produced large long (short) returns all have in common that they systematically have made new highs (lows) over time. The price of a stock cannot increase without making new highs over time and a stock price cannot decrease without making new lows over time.

Jegadeesh & Titman (1993) have shown that an investor that takes a long position in the stock that has outperformed and hold such positions for the next six months would on average made a twelve percentage annual return. Grinblatt, Titman, and Wermers (1995) found that 77 percent of the mutual funds under investigation used a momentum investment strategy i.e. buying past winners. George and Hwang (2004) and Liu et al (2010) argue that the 52-week high price explains a large portion of the profits from momentum investing. Szakmarya, Shenb and Sharmac (2010) note that trend following strategies plays an important role in the commodity futures markets. They use monthly data for 28 markets for a 48 year time period to show that a trend following strategy has produced positive returns net of transaction costs in at least 22 markets out of 28. Jamesa (2003) argues that trend following strategies is an important tool when it comes to currency trading. The author shows by looking at FX data that a simple moving average can increase returns significantly. Such a strategy also results in an increase in the information ratio. The dynamic nature seems to be the key factor explaining such performance.

Fung & Hsieh (2001) looked at empirical data for 407 trend-following funds. They found that trend following returns tends to be asymmetric which means that linear factor models might not be appropriate to analyze the performance of such funds. They also found that trend-following funds tend to do well when market crashes or rallies. Also benchmark indices as a proxy for risk might not be appropriate to use when it comes to trend-following funds due to the many different ways of implementations such basic strategy. The authors further explain that option models like look-back straddles can explain the trend following return much better than benchmark indices. This is also supported by authors such as Glosten and Jagannathan (1994) who came to the same conclusion by analyzing the performance of 130 mutual funds during the period 1968–1982.

Fung and Hsieh (2004) use eight dynamic risk factors which they show can explain up to 80% of diversified hedge funds monthly return variation. Capoccia and Hübner (2004) analyzed the performance of hedge funds by looking at a large database consisting of 2796 individual funds. They found that the general hedge fund showed little evidence of persistence in performance. However, they also found a small subsample, which was not representative for the group, that did have persistent performance. Kosowskia, Naikb and Teoc (2007) on the other hand argue that top hedge fund performance cannot be explained by luck since their performance persists on an annual basis. They also explain that Bayesian methods will produce increase performance predictability of hedge funds. Balia, Gokcanb and Liangc (2007) found that there exist a significant and positive relationship between hedge funds return and Value-at-Risk (VaR). They looked at a large dataset for the period 1995 to

2003 and discovered that funds with high VaR outperformed funds with low VaR with an annual return difference of 9%.

I.

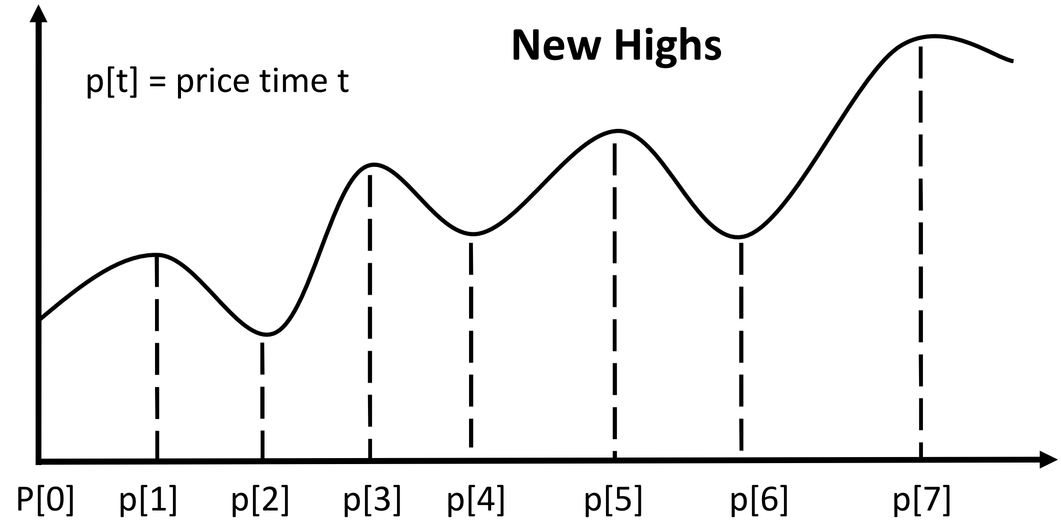
We will in this section empirically investigate the relationship between the number of new highs (low) and percentage return. We will use two different datasets. One dataset consists of monthly data for SP500 (470 Stocks) for the period 2003 -2009 and one dataset consists of monthly data for NYSE (2038 Stocks) for the period 2005-2010. In exhibit-1 you can find the summary of the regression models and its output. In exhibit-2 we can see how the number of new highs and lows are calculated. In exhibit-3 we can see the number of new highs (lows) and long (short) percentage returns. In exhibit-4 to exhibit-7 we can see the regression models for the two datasets and the cumulative return for an investor that takes a long (short) position the stock that has had the largest number of new highs (lows) during the previous period. Finally in exhibit-8 we can see the regression result where the dependent variable is the absolute percentage return and the two independent variables are the number of new highs and the number of new lows.

Exhibit-1 Data Sets and Regression Models

	SP500 (470 Stocks) 2003 -2009 Monthly Data 74 Observations	**NYSE (2038 Stocks) 2005-2010 Monthly Data 71 Observations**
Long Return and New Highs	y=a+B1*x1 y = long return, x1 = # of new highs a = -114 B1 = 7.5 TstatB1 = 8.77 (significant) Rsquare = 0.14	y=a+B1*x1 y = long return, x1 = # of new highs a = -51.8 B1 = 8.03 TstatB1 = 22.36 (significant) Rsquare = 0.19
Short Returns and New Lows	y=a+B1*x2 y = short return, x2 = # of new lows a = -53 B1 = 11.4 TstatB1 = 8.3 (significant) Rsquare = 0.12	y=a+B1*x2 y = short return, x2 = # of new lows a = -80.3 B1 = 8.19 TstatB1 = 20.28 (significant) Rsquare = 0.16

Abs Returns and New Lows and New Highs	y=a+B1*x1+B2*x2 y = abs return, x1 = # of new highs x2 = # of new lows a = -33.7 B1 = 4.96 B2 = 3.87 TstatB1 = 5.06 (significant) TstatB2 = 2.4 (significant) Rsquare = 0.05	y=a+B1*x1+B2*x2 y = abs return, x1 = # of new highs x2 = # of new lows a = -15.2 B1 = 5.86 B2 = 2.25 TstatB1 = 13.08 (significant) TstatB2 = 4.54 (significant) Rsquare = 0.09

Exhibit-2 Roadmap to Calculate New Highs and New Lows



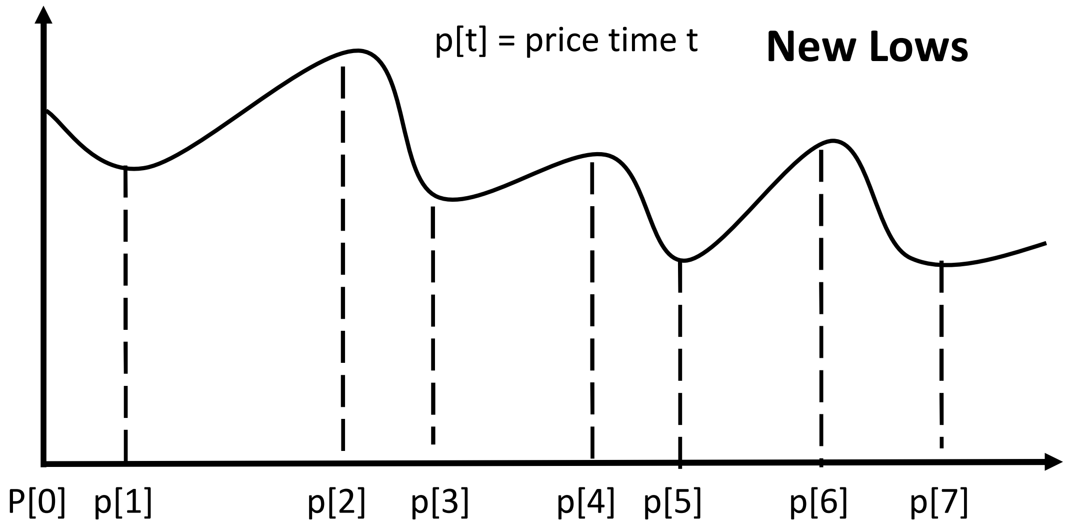
NH=# of New Highs

t=0 p[0]=max[0] and NH[0]=0

t=1 p[1]>max[t-1] -> max[t]=p[1] and NH[t] = NH[t-1] + 1 = 1

t=2 p[2]<max[t-1] -> max[t]=max[t-1] and NH[t] = NH[t-1] = 1

t=3 p[3]>max[t-1] -> max[t]=p[3] and NH[t] = NH[t-1] + 1 = 2



NL=# of New Lows

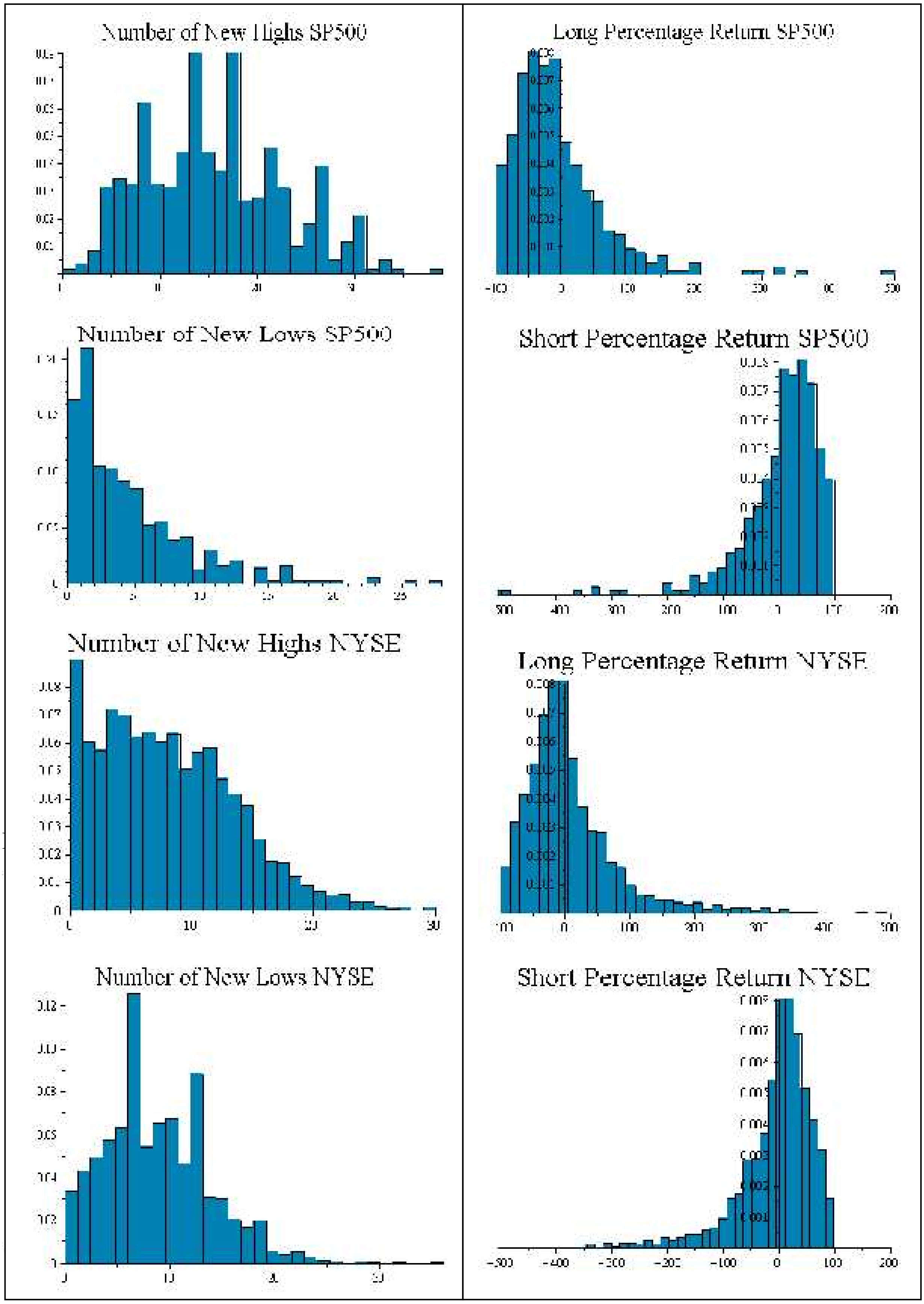
t=0 p[0]=min[0] and NH[0]=0

t=1 p[1]<min[t-1] -> min[t]=p[1] and NL[t] = NL[t-1] + 1 = 1

t=2 p[2]>min[t-1] -> min[t]=min[t-1] and NL[t] = NL[t-1] = 1

t=3 p[3]<min[t-1] -> min[t]=p[3] and NL[t] = NL[t-1] + 1 = 2

Exhibit-3 New Highs (Lows) and Long (Short) Returns for the two Datasets



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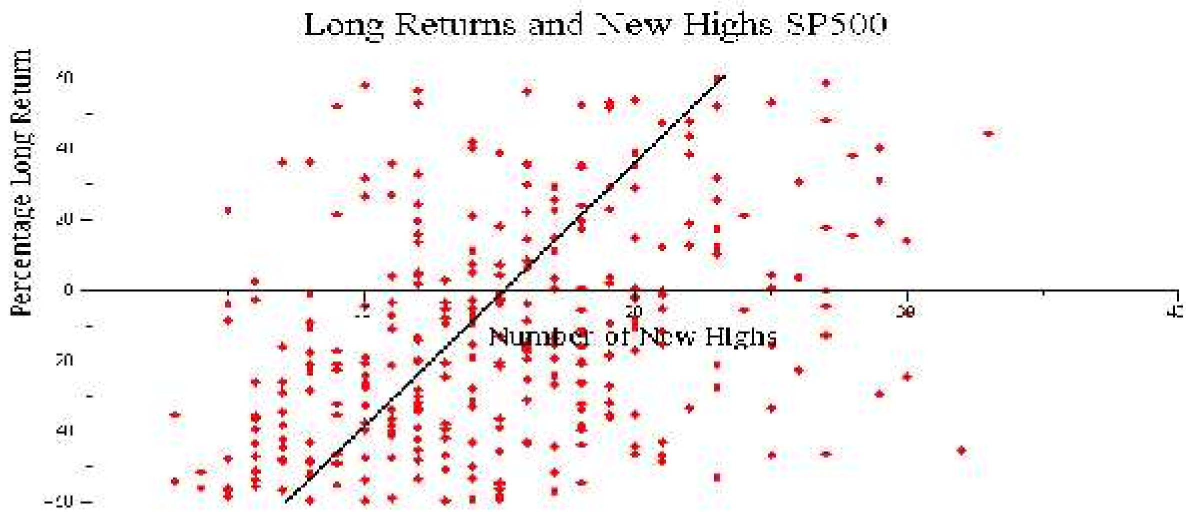
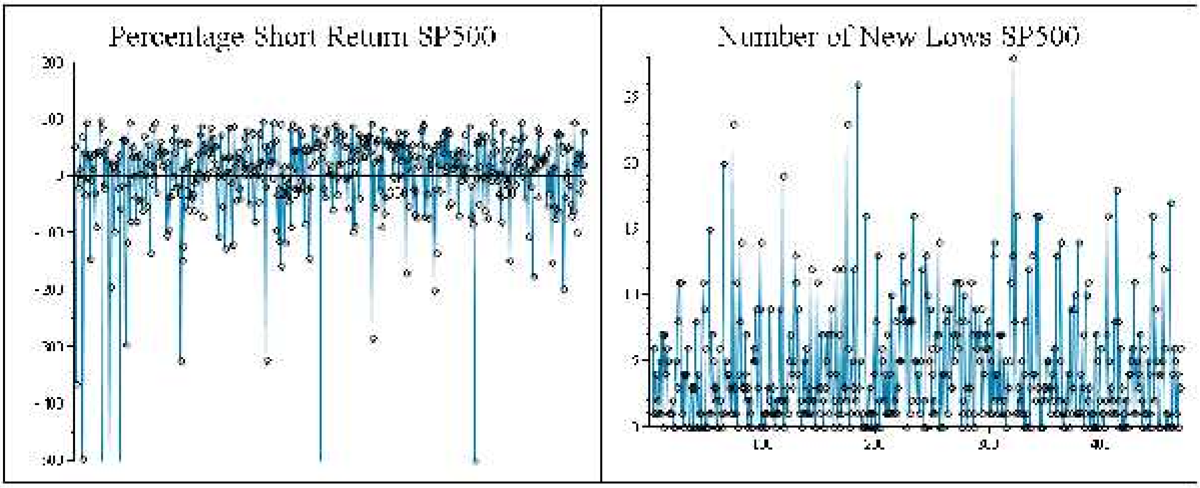
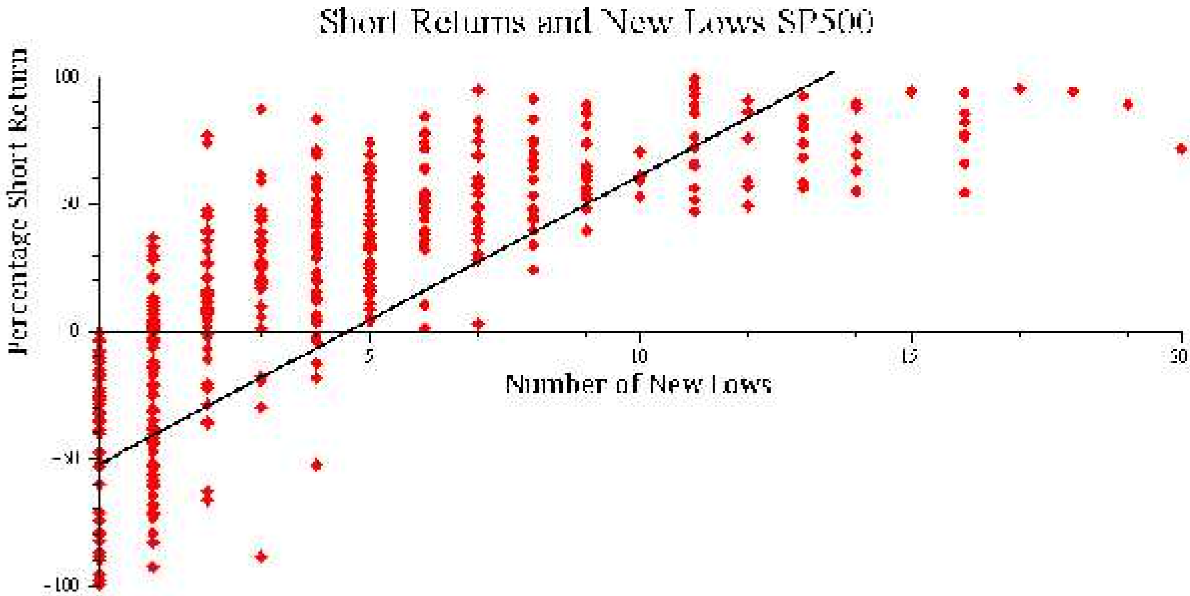


Exhibit-5 Percentage Short Returns and New Lows SP500





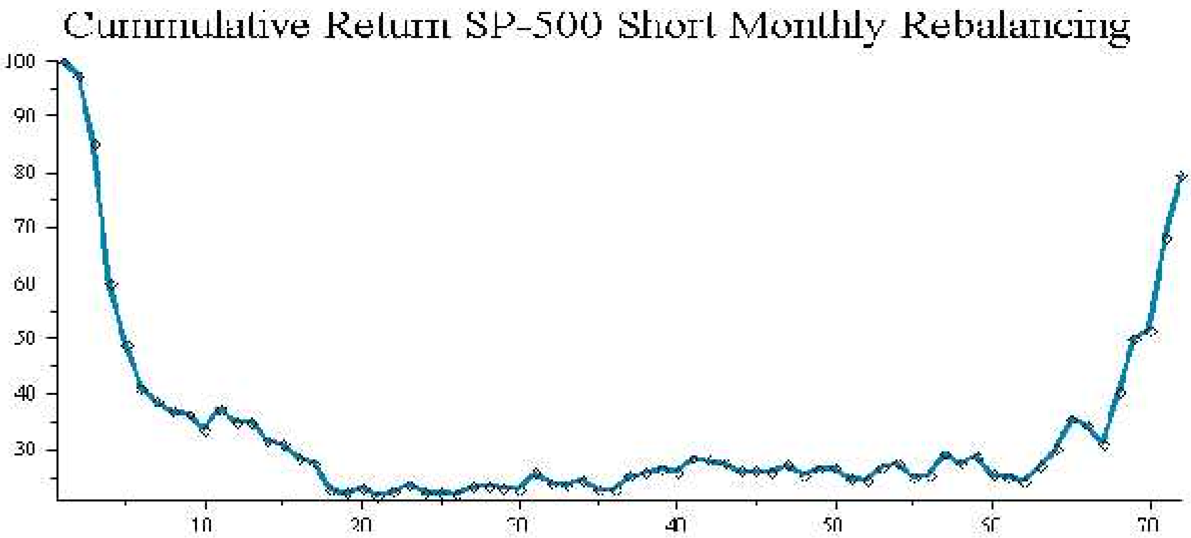
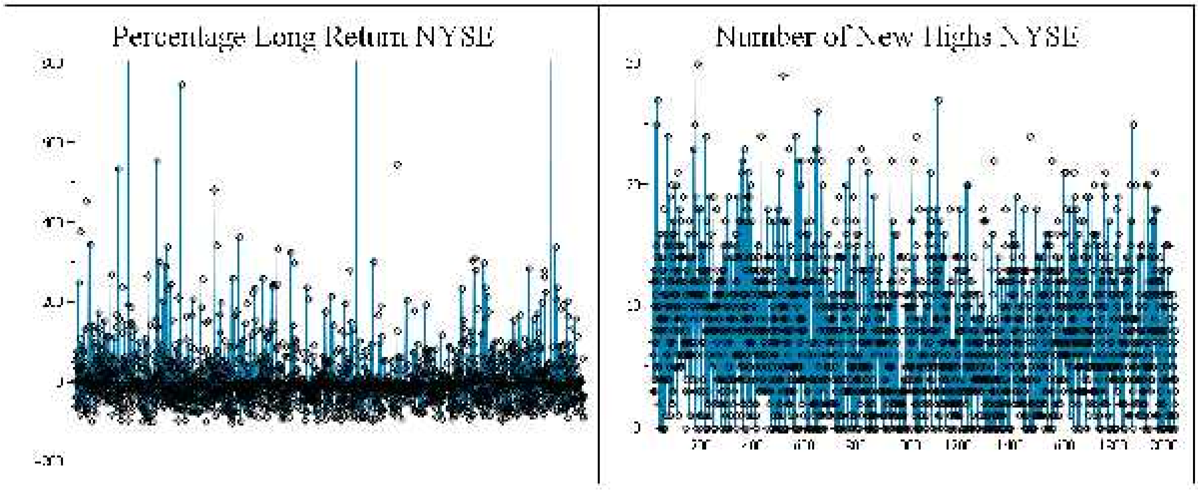


Exhibit-6 Percentage Long Returns and New Highs NYSE



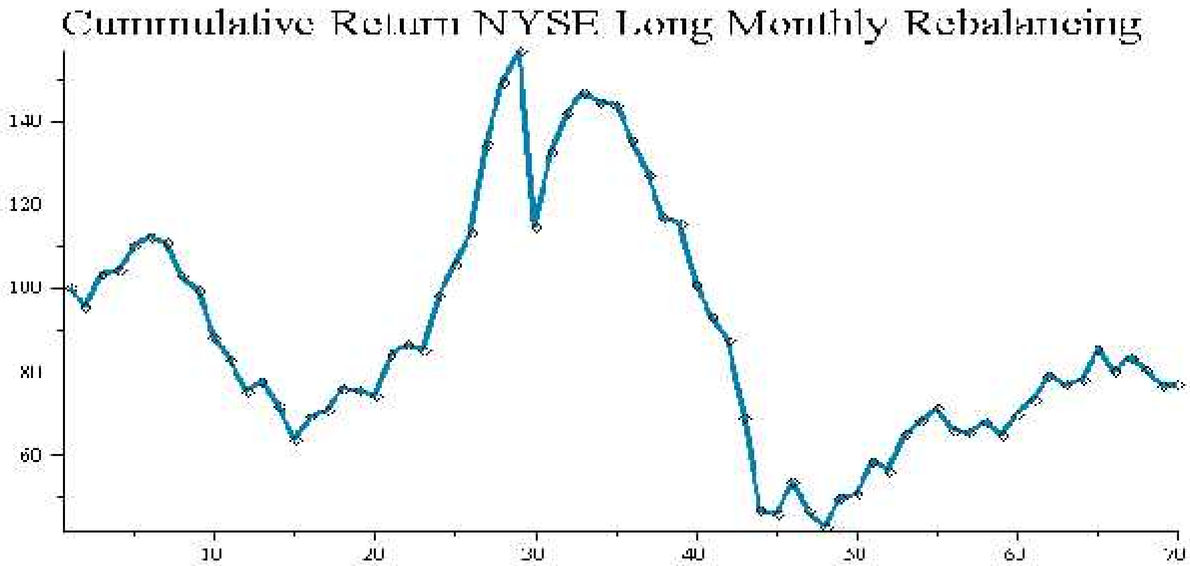
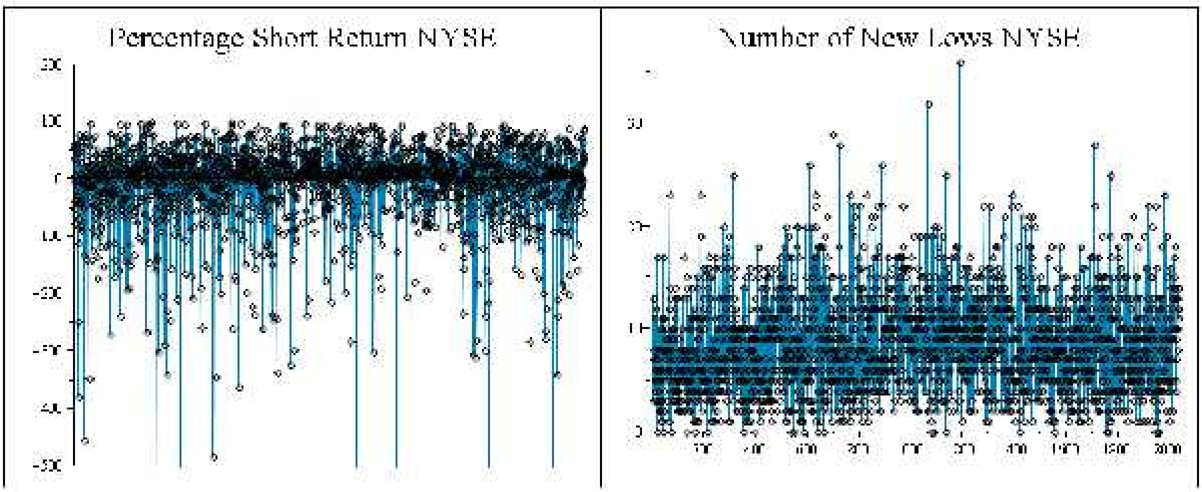


Exhibit-7 Percentage Short Returns and New Lows NYSE



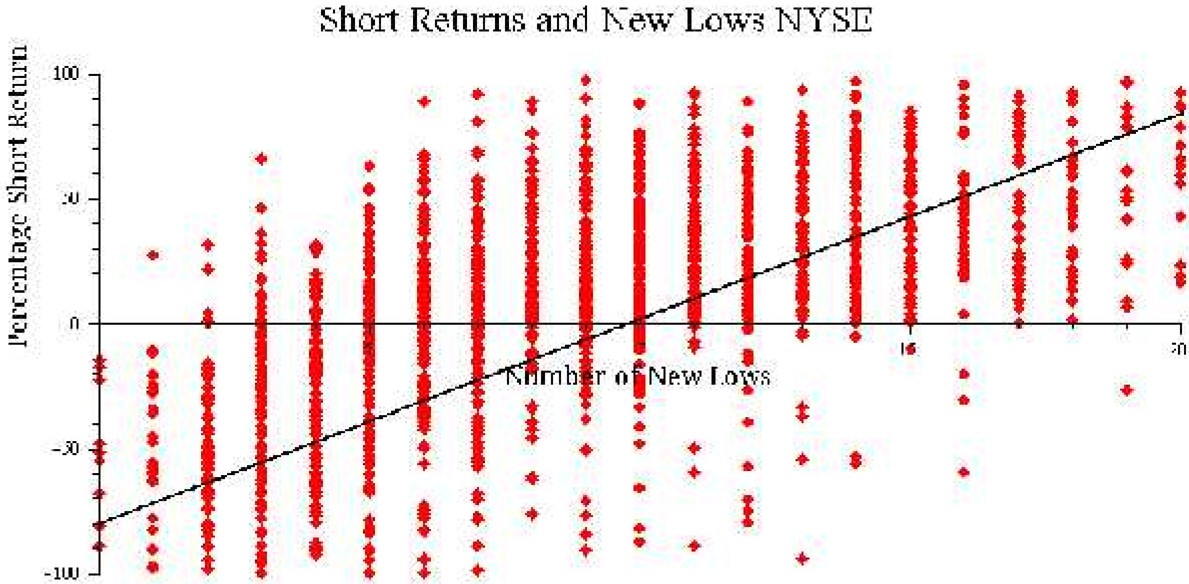
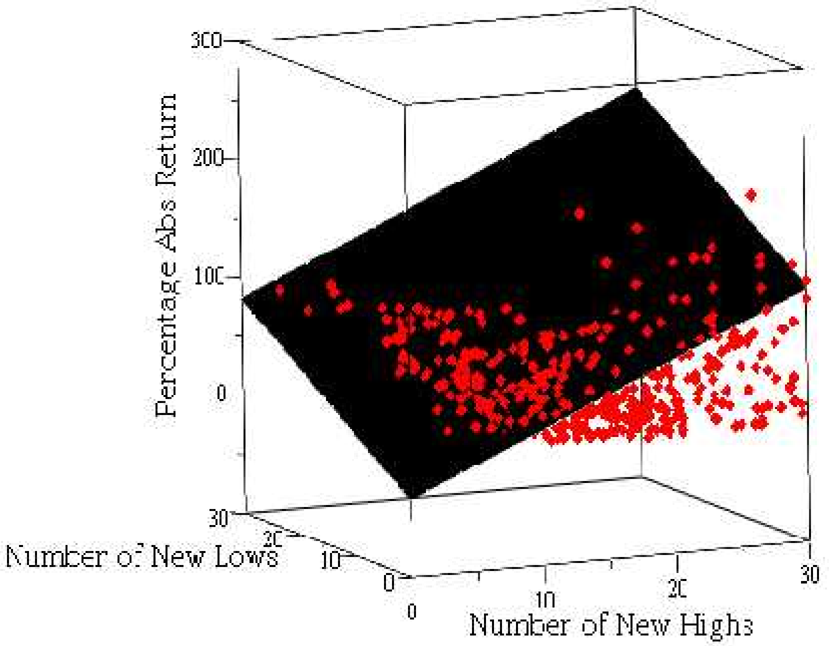
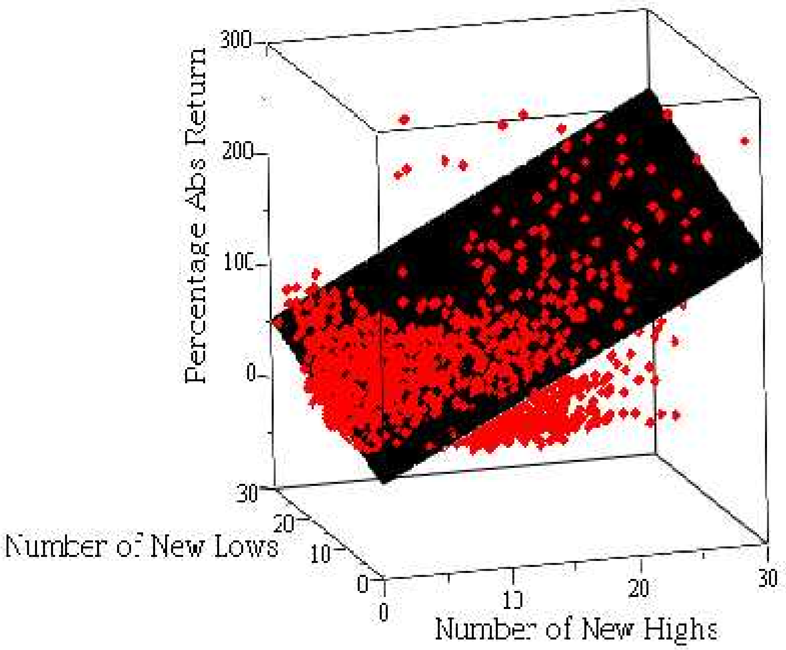


Exhibit-8 Absolute Returns and New Highs and New Lows

Abs Returns and New High and New Lows SP500



Abs Returns and New High and New Lows NYSE



Conclusion

We have in this paper analyzed the empirical relationship between the number of new highs (lows) and percentage return for a large sample of stocks. The theoretical argument is that stocks that historically have produced large long (short) returns all have in common that they systematically have made new highs (lows). See appendix-1 for further details. Hence, a stock that has a large number of new highs should also produce higher long returns than a stock with a small number of new highs. The same argument does also apply to short positions. The short return is simply -1*long return. We have seen in exhibit-1 that the variable the number of new highs is highly significant for the two dataset which means that the number of new highs can explain a lot of the variation in long percentage returns. The Rsquare was 0.14 and 0.19 for the two models. The variable the number of new lows was also highly significant for the two dataset which means that the number of new lows can explain a lot of the variation in short percentage returns. The Rsquare was 0.12 and 0.16 for the two models. The relationship between the number of new highs (low) and long (short) percentage returns is marginally stronger (weaker) due to differences in Rsquare. What was not expected was the low Rsquare (0.05 and 0.09) for multiple regression where the dependent variable was absolute percentage returns and the two independent variables where the number of new highs and the number of new lows. One would have expected a higher Rsquare than these models separately, however that was not the case. If we interpret the absolute return as volatility it makes more sense since volatility and new high (lows) usually don't go together. We can also see in appendix-2 how the number of new highs (lows) changes over time for different stocks included in the datasets. In appendix-3 a new dataset is introduced which consists of monthly data from 1997-2010 for 23 global stock market indices. We can see the cumulative return for an investor that takes a long (short) position the market that has had the largest number of new highs (lows) during the previous period.

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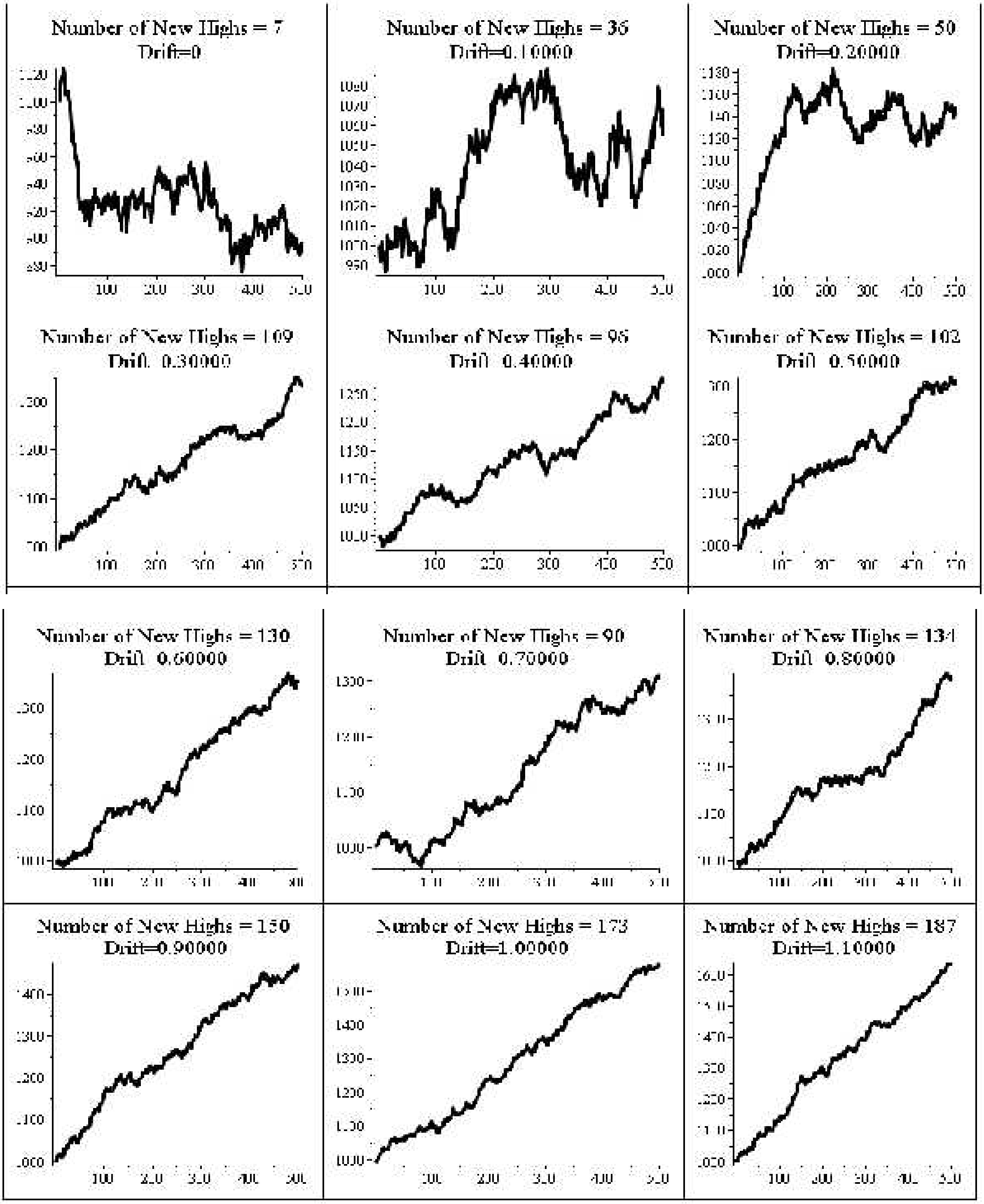
Appendix-1 Simulated Data and Number of New Highs

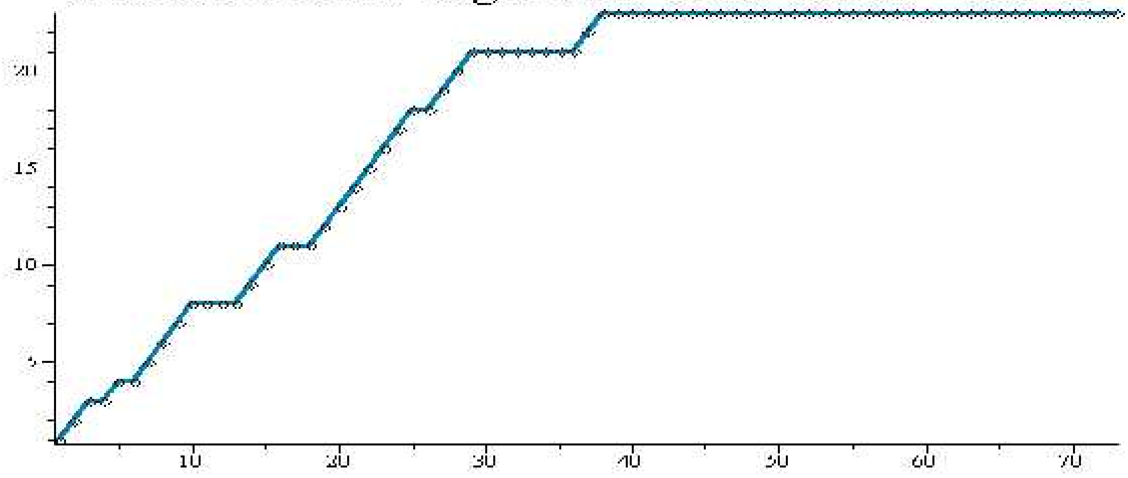
Drift	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0	1.1
Number of New Highs	7	36	50	109	96	102	130	90	134	150	173	187
Percentage Return	10	5	14	34	28	30	35	31	38	48	58	64

"Correlation Between Number of New Highs and Percentage Return" = 0.98802

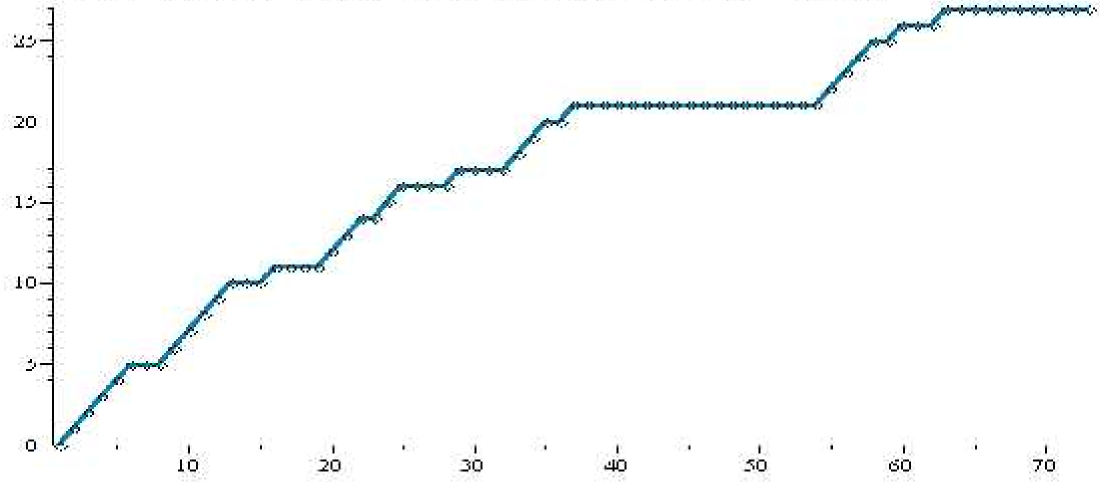


Appendix-2 Number of New Highs (Lows) over Time

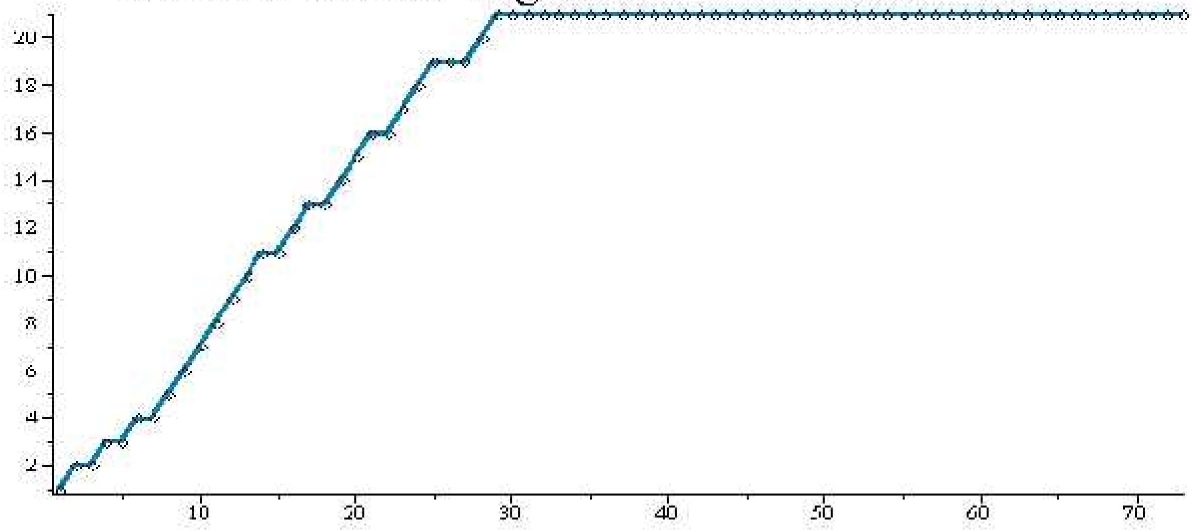
Number of New Highs over Time Ticker =MAR

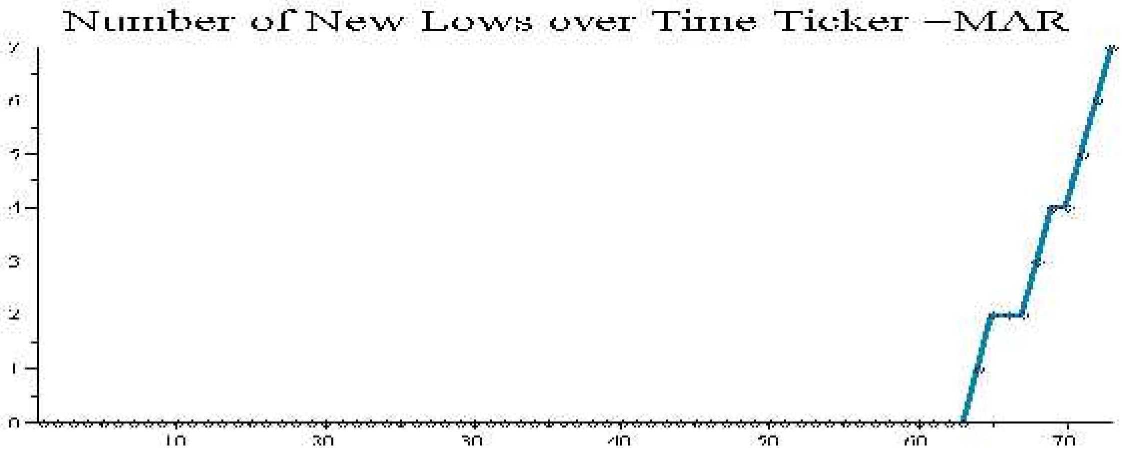


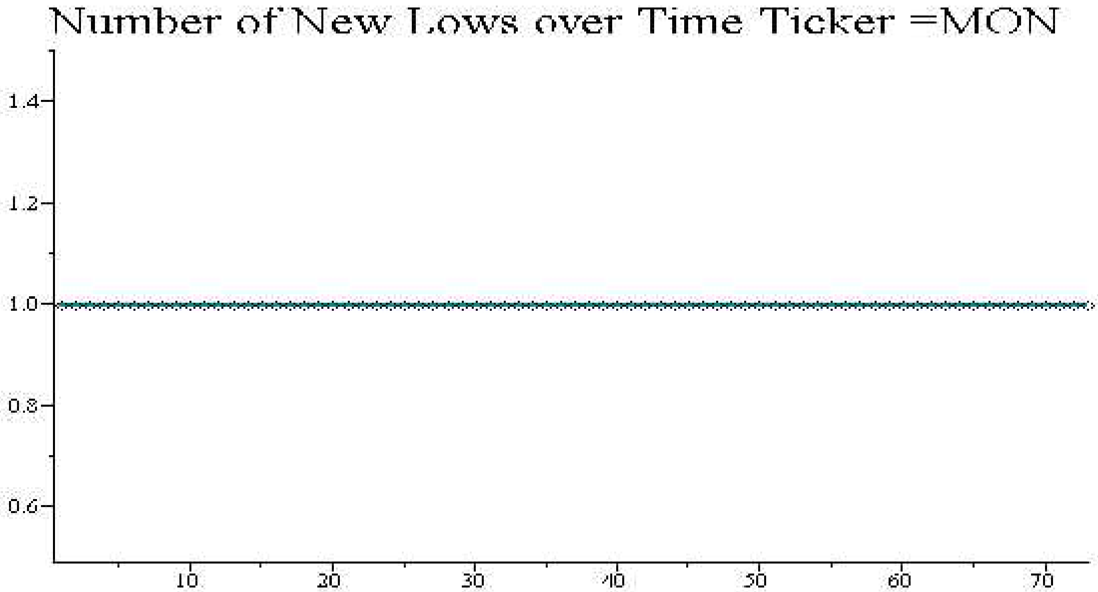
Number of New Highs over Time Ticker =MON

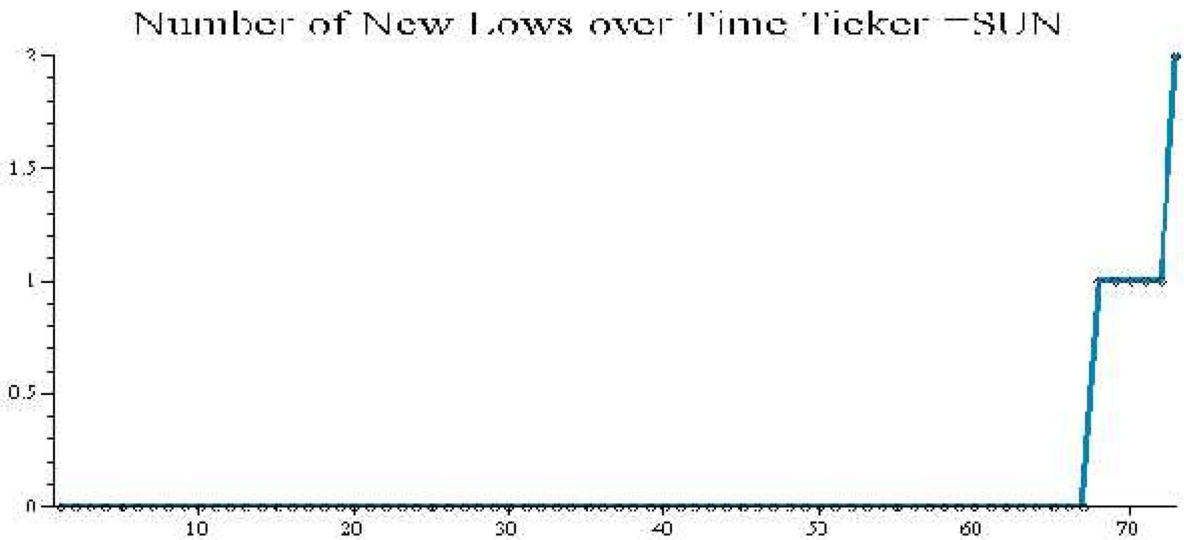


Number of New Highs over Time Ticker =SUN




Number of New Lows over Time Ticker =MAR


Number of New Lows over Time Ticker =MON
1.4
1.2
1.0
0.8
0.6
10
20
30
40
50
60
70


Number of New Lows over Time Ticker =SUN
1.5
1
0.5
0
10
20
30
40
50
60
70

Appendix-3 Global Stock Market Indices Dataset

Monthly data from 1997-2010 for 23 global stock market indices

["^AEX" "^AORD" "^ATX" "^BSESN" "^BVSP" "^CCSI" "^DJI"]

["^FCHI" "^FTSE" "^GDAXI" "^GSPC" "^HSI" "^JKSE" "^KLSE"]

["^KS11" "^MERV" "^MXX" "^N225" "^SSEC" "^SSMI" "^STI" "^TA100"]