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Is the January Barometer a Reliable Indicator?

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Abstract

The January Barometer, which suggests that positive (negative) market returns in January predict positive (negative) returns in the following eleven months of the year, is examined using historical price data for three major market indices; the S&P 500 index, the NASDAQ 100 index, and the Russell 2000 index. For the 50-year period 1968-2018, it is found that there is a correlation between positive January returns on the S&P 500 and positive market performance for both February and the rest of the year, particularly when the Index has gained at least 4% in January. However, a down January is not a reliable predictor of an overall weak year. The same study over the 25-year period 1993-2018 shows that the success rate of a positive signal from the January Barometer as an indicator of future performance has diminished in the most recent 25-year period. A similar analysis for the NASDAQ 100 index over the 32-year period 1986-2018 shows that a negative January return does not exhibit any predictive significance, while a January gain primarily affects the magnitude of gains for the rest of the year, without any significant effect on the success rate. The January performance of the NASDAQ 100 index does not have any short-term predictive significance. Analysis of the Russell 2000 price data over the 31-year period 1987-2018 shows that a positive January return of at least 4% is a very good indicator of the Index's return for the rest of the year, whereas a negative return in January is not a reliable indicator of weak future returns. For both NASDAQ 100 and Russell 2000, it is found that January return is a much better indicator of their summer performance than their returns for the rest of the year.

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Chapter 1

Introduction

At the beginning of each year, you may hear many economists and pundits predicting how the stock market is going to turn out for the new year. One of the ways these "experts" make their predictions is by using an indicator called the *January Barometer*. The January Barometer is based on a simple idea that basically compares the movement of the S&P 500 index at the end of January to where it was at the end of the previous December. If the Index is higher at the end of January, then the hypothesis is that the stock market will rise that year. If the Index is lower at the end of January, then it is bad news for the equity markets.

You might think this is just voo-doo economics or a myth similar to the groundhog seeing its shadow. However, if you think about it, the argument does seem to have some merit. For example, the economy grows when people spend money, and people are usually broke in January as they pay off their Christmas purchases. Therefore, if the stock market is up at the end of January, presumably because the economy is actually growing at that time, it would tend to indicate that it is going to be a good year for the stock market.

On the other hand, you might also argue that if the premise of the January Barometer were true, this would imply that January returns have predictive power over the returns of the following eleven months, and that would be an anomaly on the Efficient Market Hypothesis. The weak-form of the Efficient Market Hypothesis states that using old stock price/return data cannot predict future stock prices/returns, because the information from such data has already been included in current stock prices through trading [1]. Therefore, using the January Barometer as a trading strategy should not be able to generate excess returns, according to theory. Still, the January Barometer effect could exist as a temporary anomaly that would eventually disappear as investors recognize the pattern and try to exploit it.

The topic I have chosen for my research paper is the January Barometer. The question that I want to answer is whether or not the January Barometer is economically significant as a market indicator – i.e. can it be traded profitably? If so, is it a better indicator for a particular sector of the stock market (large cap vs. small cap stocks) or over a specific time interval (as an indicator of forward monthly, quarterly, or annual returns).

Chapter 2

Literature Review

The existence of seasonality in stock prices has important implications for capital market theory, capital market efficiency, and the distribution of stock returns. However, the subject did not receive much attention in the literature until the 1960s, mainly because early research on the subject had indicated quite conclusively that seasonal movements were nonexistent. For example, a comprehensive study of an index of stock prices from 1897 to I9I4 had revealed absolutely no evidence of seasonal tendencies, as reported by the Harvard Committee on Economic Research in 1919 [2]. Owens and Hardy [3] extended the Harvard committee's work by including stock price data for an additional decade, and found similar results. They argued that seasonal variations of stock prices are impossible because if they did exist, general knowledge of their existence would put an end to it.

Despite the dogmatic conclusion of Owens and Hardy, which seemed sufficient to close the issue for good, the question of whether individual stock prices display seasonal movements remained clouded for two major reasons. First, virtually no attention had been devoted to individual stock prices. Findings of little or no seasonality in stock price indices do not necessarily hold for individual stock prices because different seasonal patterns in the price of individual stocks can offset one another to yield little or no seasonality in the composite index. Second, various observations of market seasonality in the ensuing decades produced apparently conflicting findings, and once again brought the issue back into the spotlight. For example, a published report by Fenner and Beane (one of the country's larger investment houses) in 1939 showed strong bullish tendencies in stock prices during 14 of the 15 summers from I924 to I939 [4]. Similarly, examination of the Dow- Jones Industrial Average from I927 to 1942 showed frequent bullish tendencies in this index from December to January, with considerable appreciation (up to $5?10\%$ in many instances) in 11 of these 15 years and relatively insignificant bearish tendencies (less than 4%) in the remaining four years [4].

The only substantial study of seasonality in individual stock prices before the 1960s was Wachtel's investigation of vear-end price behavior of high-yieldinq stocks [3]. While his findings were positive, they were not sufficient to justify his conclusion that seasonal trading had a high probability of success. Prompted by the availability of computers, studies of seasonality in individual stock prices began appearing in the 1960s. Granger and Morgenstern [5, 6] performed spectral studies

on first-differenced price data and concluded that the folklore of seasonality in stock prices was disproved. Their findings were in conflict with later studies that did find seasonality. In particular, Bonin and Moses [7] found a significant seasonal component and objected to the methodology used by Granger and Morgenstern. Similarly, Rozeff and Kinney [8] analyzed monthly rates of return on the New York Stock Exchange from 1901-1974 and presented evidence of the existence of seasonality. They found that with the exception of the 1929-1940 period, there were statistically significant differences in average returns for different months, due primarily to unusually high January returns.

There was a proliferation of empirical studies in the 1980s documenting anomalous behavior in stock prices such as seasonal tendencies associated with the time of the day [9], the day of the week [10, 11, 12, 13, 14], the time of the month [15], and the turn of the year [16, 17, 18, 19]. The results of these studies presented a challenge to classical models of market equilibrium, but Lakonishok and Smidt [20] argued that it was at least possible that the new findings were really produced by sampling error, noise, and data snooping (i.e. using the same data to both discover and test hypotheses). As such, they set out to check for the existence of seasonal anomalies over a longer period of time than that used in other studies. They used 90 years of daily closing price data on the Dow-Jones Industrial Average (from 1897 to 1986 – practically the entire time the U.S. stock index had existed) to test for the existence of persistent seasonal patterns in the rates of return. They found evidence of persistently anomalous returns around the turn of the week, around the turn of the month, around the turn of the year, and around holidays. However, they found the magnitude of the seasonal anomalies to be much smaller than the size of a tick (the smallest price change, which was 12.5 cents at the time). Because the average price per share of a stock on the New York Stock Exchange (NYSE) was about 40 at the time, a movement of one tick represented at least a 0.31% price change, which was much greater than the seasonal anomalies quantified by Lakonishok and Smidt.

Among the seasonal anomalies discovered in stock returns, the turn-of-the-year (TOY) effect generated the greatest interest in the 1980s. The TOY effect, also called the "January effect", refers to the phenomenon that stock returns are higher, on average, in January than in other months. For example, Rozeff and Kinney [8] found an average return of 3.48% for the month of January

compared to only 0.42% per month for the other eleven months. As was first documented by Banz [21], and later extended and refined by others [22, 23, 24], the January seasonal effect is highly sensitive to stock capitalization, and hence to the index used. Low-capitalization ("small") stocks display unusually high average returns during the period beginning on the last trading day of December and continuing through January, with the effect becoming progressively less pronounced as the month wears on. High-capitalization ("large") stocks, on the other hand, do not have higher returns in January than in other months. For example, during 1971-1985, the average difference in returns between small and large stocks (defined as the smallest and largest deciles of market value on the NYSE) was 8.17% for the first nine trading days of the year [25].

A number of reasons were proposed to explain the January effect, most notably the tax-loss-selling hypothesis which attributes the TOY effect to the buying and selling behavior of individual investors at year end. Namely, as the end of the year approaches, individual investors sell under-performing stocks in order to realize the losses for tax purposes. However, the proceeds from the sales are not immediately reinvested, but are held until January. When the funds are reinvested in January, the buying pressure drives up the price of small stocks in which individual investors typically invest. Although tax-loss selling was advanced as the cause of the January effect, the persistence of this phenomenon in overseas markets with tax years that do not start in January suggests that the January effect may be in part a calendar effect induced by the turn of the year.

The other January effect, called the "January Barometer" to distinguish it from the TOY effect described above, was coined by the Stock Trader's Almanac back in 1972. It states "As the S&P 500 (SPX) goes in January, so goes the year." It posits that a gain for the SPX at the end of January tends to be bullish for stocks by the end of the year, whereas a negative January return warns of bearish implications for the market. It has been touted as a guide to investing in the stock market since at least 1973 and has appeared regularly in the financial press ever since. Many traders look to this barometer, among other indicators, to forecast the market climate for the whole year. Traders who are too impatient to wait for the end of January use the "First Five Days" indicator (based on SPX performance in the first five trading days of the year) as an early warning system for insight into full-year market performance.

The January Barometer is believed to have its origins in the 20th Amendment to the Constitution, which moved Inauguration Day from March 4 to January 20 and changed the day newly elected senators and representatives take office. As such, January's prognostic power is attributed to a number of important events taking place during the first month of the year. These include the President's State of the Union address and presentation of the annual budget, both of which set national goals and priorities that affect the economy and Wall Street. In fact, increased cash inflows and portfolio adjustments at the beginning of the year are additional factors cited as contributors to the January Barometer. Finally, January is anchor to the best consecutive three-month span for the market, i.e. November through January, presumably giving market action in January additional significance.

There have been several studies of the January Barometer as a valuable signal for the market returns in the following eleven months of the year (cf. [26, 27, 28, 29, 30, 31]. The rest-of-year (ROY) returns (as opposed to full year returns) are examined to address the concern that a significant portion of the full-year returns might be accounted for by the month of January itself. In other words, by the time one acts on a signal from the Barometer, the market has already moved significantly. To support the January Barometer, there needs to be both positive returns for January and the ROY, or both negative returns for January and the ROY. Hensel and Ziemba [27] investigated the validity of the January Barometer using monthly returns on the S&P 500 during the 68-year period $1926 - 1993$. They concluded that the January Barometer has good predictive power. Brown and Luo [29], on the other hand, argued that the January Barometer fails when January is an up month and one decides to be in the stock market for the next 11 months. More recently, Dzhabarov and Ziemba [31] examined the ROY returns versus January returns for the S&P 500 over the 70-year period 1940-2009. They found that over the 70-year period, when January returns were positive, the ROY return was also positive 86.4% of the time. A naive model that simply predicted an up market every year would have been correct 71% of the time over the same period. When the January returns were negative, Dzhabarov and Ziemba found that the whole year was up 50% of the time, significantly lower than the 71% proportion of years in which the market was up for the whole year.

Year	January Return (%)	Full Year Return (%)
2009	-8.6	$+26.5$
1970	-7.6	$+4.0$
1960	-7.1	$+0.5$
1990	-6.9	-3.2
1978	-6.2	$+6.6$

Table 2.1: Worst January returns on record for the S&P 500 index

While some studies have shown the January Barometer to have better than a 50% accuracy rate over a long time period, others have pointed to the January Barometer's shortcomings in more recent years to argue that it is flawed. For example, just using the last nine years of Dzhabarov and Ziemba's data (from 2001-2009), the January barometer fell short in accuracy with a score of five to four. Similarly, consider the full-year performance of the S&P 500 index following its five worst January returns on record, shown in Table 2.1. Clearly, five of the six years containing terrible January returns ended up as profitable years in the market.

This report extends the analysis of Dzhabarov and Ziemba [31] by including price data through February 2019 for the S&P 500 index. It also examines seasonal tendencies that might be associated with a "January Barometer" for the NASDAQ 100 and the Russell 2000 stock indices, as well as the three most actively traded exchange traded funds (ETFs) designed to track the performance of the aforementioned major stock indices.

Chapter 3

Results & Discussion

3.1 S&P 500 Index

Table 3.1 shows a comparison of the ROY returns (from February through December) on the S&P 500 for years with positive and negative January returns in the last 50 years. During that time period, there were 29 years with positive January returns and 21 years with negative January returns. When the S&P 500 was up in January, the index registered a positive ROY return 83% of the time, compared to 62% for years with a down January. The average ROY return following an up January was an impressive 10.6%, in stark contrast to less than 2% return in other years. The median ROY return for years with an up January outshined its down-January counterpart by an even wider margin, reflecting the much smaller percentage of negative ROY returns in such years. The large difference between the average ROY performance figures is due to larger and more frequent ROY losses in down years following a down January, as shown by a comparison of the mean negative ROY returns in Table 3.1. The average negative ROY return for years with a down January, as well as the percentage of negative ROY returns in such years, were nearly twice their corresponding values for years following an up January, while the average positive returns were about the same in the two cases.

	Positive January Return	Negative January Return
Mean Return (%)	10.6	1.6
Median Return (%)	13.5	2.5
Mean Positive Return (%)	14.6	12.5
Mean Negative Return (%)	-8.8	-16.2
Number of Years	29	21
Percent Positive	83	62

Table 3.1: S&P 500 ROY returns $(1968$ - $2018)$

	$> 4\%$ January Gain	$> 4\%$ January Loss
Mean Return (%)	11.7	1.6
Median Return (%)	16.0	0.4
Mean Positive Return (%)	15.4	13.3
Mean Negative Return (%)	-10.5	-13.0
Number of Years	14	9
Percent Positive	86	56

Table 3.2: S&P 500 ROY returns following $4\%+$ January gains/losses (1968 - 2018)

Does the magnitude of January's gain or loss affect the results of Table 3.1? Has the January Barometer been a more reliable indicator in years when January's positive or negative return was unusually large (such as the $> 4\%$ return achieved by the S&P 500 in January of 2019)? To answer this question, Table 3.2 summarizes a comparison of the ROY returns on the S&P 500 index for years with positive or negative January returns in excess of 4% during the last 50 years. During that time period, there were a total of 23 years in which January was either up (14 occurrences) or down (9 occurrences) by more than 4%. Within those two clusters, the index registered a positive ROY return 86% of the time when January was up, and 56% of the time when January was down. This is about the same success rate as that reported earlier in Table 3.1 for any up/down January. The average and median ROY returns following a $4\%+$ up January were respectively about 10% and 20% higher than the corresponding results for any up January. The average ROY return for years with a $4\%+$ down January was identical to that for any negative January, while the median ROY return dropped to zero. The large gap in the average negative ROY returns of the down-January and up-January data narrowed compared to the results in Table 3.1, though the number of signals with negative ROY return is too small to make this observation statistically significant. Overall, the magnitude of January's gain or loss seems to have little or no effect on the effectiveness of the January Barometer.

	Positive January Return	Negative January Return
Mean Return (%)	1.1	−1.0
Median Return (%)	1.1	−1.7
Mean Positive Return (%)	3.0	2.9
Mean Negative Return (%)	−3.3	−3.4
Number of Years	29	21
Percent Positive	69	38

Table 3.3: S&P 500 February returns (1968 - 2018)

How about short-term performance (e.g. next month or next quarter returns)? For example, were January returns a better indicator of February returns rather than ROY returns? Table 3.3 shows a comparison of February returns on the S&P 500 following positive and negative January returns in the last 50 years. It appears that January performance of the S&P 500 index has been a very good indicator of its February returns. Positive S&P 500 returns in January have led to an average gain of more than 1% in February with about a 70% success rate (i.e. 70% of returns positive), while a down January has resulted in an average loss of 1% on the index with more than 60% of the returns negative.

Table 3.4 provides a summary of February performance on the S&P 500 index for years with positive or negative January returns in excess of 4%. Compared to any positive January, the average gain on the S&P 500 index in February is larger when January is up by more than 4%. Similarly, the index suffers a bigger average loss in February (compared to that for any down January in Table 3.3 when January is down more than 4%. Based on these results, the January Barometer appears to have been a better indicator of February performance than ROY performance, at least for the S&P 500 index.

The difference between the average monthly returns of the S&P 500 index in up-January and down-January years is shown in Figure 3.1 for the remaining months of the year. When January

	$> 4\%$ January Gain	$> 4\%$ January Loss
Mean Return (%)	1.2	-1.6
Median Return (%)	0.9	-2.0
Mean Positive Return (%)	3.1	2.5
Mean Negative Return (%)	-2.3	-3.6
Number of Years	14	9
Percent Positive	64	33

Table 3.4: S&P 500 February returns following $4\%+$ January gains/losses (1968 - 2018)

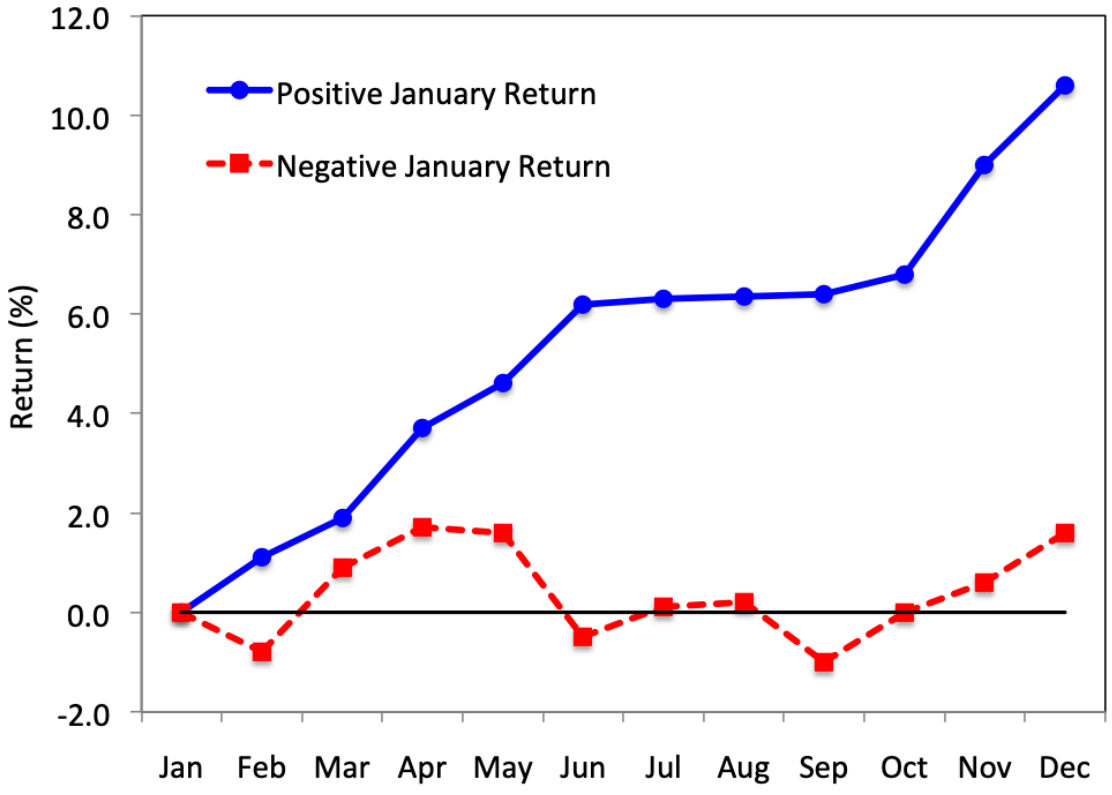

Figure 3.1: S&P 500 average monthly returns (1968-2018)

returns have been positive on the S&P 500, the index has monotonically moved higher through the rest of the year, with a flat period from August to October. This is in stark contrast to the average monthly performance of the index in years with negative January returns, which has resulted in an average path that bounces around the breakeven line for most of the year. According to this figure, the January Barometer has been a good indicator of S&P 500 performance, especially during the first half of the year.

3.2 SPY Exchange Traded Fund

Exchange Traded Funds tracking various stock market indices have become available for trading in the US since 1993. These stock-like investment funds operate with an arbitrage mechanism designed to keep them trading close to their net asset values. They trade on stock exchanges, and combine the valuation feature of mutual funds with the tradability feature of stocks. The largest ETF in the world is the Standard & Poor's Depositary Receipts (NYSE: SPY), which were introduced in January 1993. Known as SPDRs or "Spiders", SPY shares track the movements of the S&P 500 index. Other heavily-traded ETFs include the "Cubes" (NASDAQ: QQQ), which were launched in 1999 to track the movements of the NASDAQ-100 index (NDX), as well as IWM which tracks the Russeil 2000 index (RUT).

It is interesting to examine whether the introduction of the SPY ETF has had a significant effect on the aforementioned seasonal trends in the S&P 500 index. To that end, the performance of SPY since its inception in 1993 is analyzed in Tables 3.5-3.6. The ROY returns on SPY for years with positive and negative January returns are shown in Table 3.5. A comparison of the data in Tables 3.5 and 3.1 shows that the proportion of years with positive January returns was almost exactly the same before and after the inception of the SPY ETF. In the past 25 years, the median ROY return following an up January was 11.1%, nearly the same as the 10.4% return in other years. The average positive ROY return for years with an up January was actually slightly smaller than that for years with a down January. The main difference between the up-January and down-January signals during that time appears to be the much larger ROY losses (on average) in down years following a down January, as shown by a comparison of the mean negative ROY returns in Table 3.1. The average negative ROY return for years with a down January was nearly three

times the corresponding value for years following an up January. While the average ROY return for the up-January signal was about 70% higher than that for the down-January signal, there was essentially no difference in the success rate in the two cases; namely, the index registered a positive ROY return 73% of the time when the S&P 500 was up in January, compared to 70% for years with a down January. Thus, if anything, these data indicate that the reliability of the January Barometer as an indicator of ROY performance for the S&P 500 index has diminished in the quarter century following the introduction of the SPY ETF.

	Positive January Return	Negative January Return
Mean Return (%)	9.6	5.7
Median Return (%)	11.1	10.4
Mean Positive Return (%)	16.3	17.0
Mean Negative Return (%)	-9.0	-20.8
Number of Years	15	10
Percent Positive	73	70

Table 3.5: SPY ROY returns (1993-2018)

Table 3.6 shows the corresponding comparison of the ROY SPY returns for years with positive or negative January returns in excess of 4%. Since the inception of the SPY ETF, there have been a total of 9 years in which January was either up (5 occurrences) or down (4 occurrences) by more than 4%. Within those two small samples, the index registered a positive ROY return 60% of the time when January was up, compared to 50% of the time when January was down. Notwithstanding the small sample sizes, this is about the same success rate as that predicted by a fair coin. The average and median ROY returns following a $4\%+$ up January were actually substantially smaller than the corresponding results for any up January. These results suggest that basing the January Barometer on extreme January gains or losses would not have improved its reliability during the last 25 years.

	$> 4\%$ January Gain	$> 4\%$ January Loss
Mean Return (%)	5.5	2.4
Median Return (%)	8.5	4.7
Mean Positive Return (%)	18.5	25.0
Mean Negative Return (%)	-14.0	-20.2
Number of Years	5	4
Percent Positive	60	50

Table 3.6: SPY ROY returns following $4\%+$ January gains/losses (1993-2018)

	Positive January Return	Negative January Return
Mean Return (%)	0.6	-0.3
Median Return (%)	1.1	-0.7
Mean Positive Return (%)	2.8	3.9
Mean Negative Return (%)	-4.3	-3.0
Number of Years	16	10
Percent Positive	69	40

Table 3.7: SPY February returns (1993-2018)

Clearly, the January Barometer's reliability as an indicator of ROY performance on the S&P 500 index seems to have suffered a major setback following the introduction of the SPY ETF. Its relevance as an indicator of short-term performance has also diminished in the past 25 years, as shown by the results in Tables 3.7 and 3.8. Table 3.7 shows a comparison of SPY's February returns following positive and negative January returns. A comparison with Table 3.3 shows that

	$> 4\%$ January Gain	$> 4\%$ January Loss
Mean Return (%)	-0.6	-3.7
Median Return (%)	1.1	-2.1
Mean Positive Return (%)	2.5	$--$
Mean Negative Return (%)	-6.6	-3.7
Number of Years	6	4
Percent Positive	67	0

Table 3.8: SPY February returns following $4\%+$ January gains/losses (1993-2018)

the reported success rates are qualitatively similar for the 25 years before and after the inception of the SPY ETF, but the difference between average February returns following up-January and down-January signals has weakened. Positive SPY returns in January have led to moderate gains in February about 70% of the time, while negative January returns have resulted in negative February returns 60% of the time. Hence, SPY's (and hence S&P 500's) positive January performance has remained a good indicator of its positive February returns. The reliability of a negative signal improves dramatically when the January Barometer is based on $4\%+$ January gains or losses (see Table 3.8); namely, a January loss of at least 4% in SPY has resulted in negative February returns 100% of the time in the last 25 years.

Figure 3.2 lays emphasis on the difference between average SPY returns in the remaining months of up-January and down-January years. During the past 25 years, the average monthly return of SPY in the first nine months of the year has been relatively insensitive to SPY's January returns, in contrast to the behavior shown in Figure 3.1 for the past 50 years. When January has been positive, SPY has experienced a stronger advance in the last three months of the year, qualitatively similar to the behavior exhibited by the 50-year average shown in Figure 3.1. Comparison of Figures 3.2 and 3.1 is consistent with the notion that the introduction of the SPY ETF has had an adverse effect on the January Barometer's reliability as an indicator of future performance.

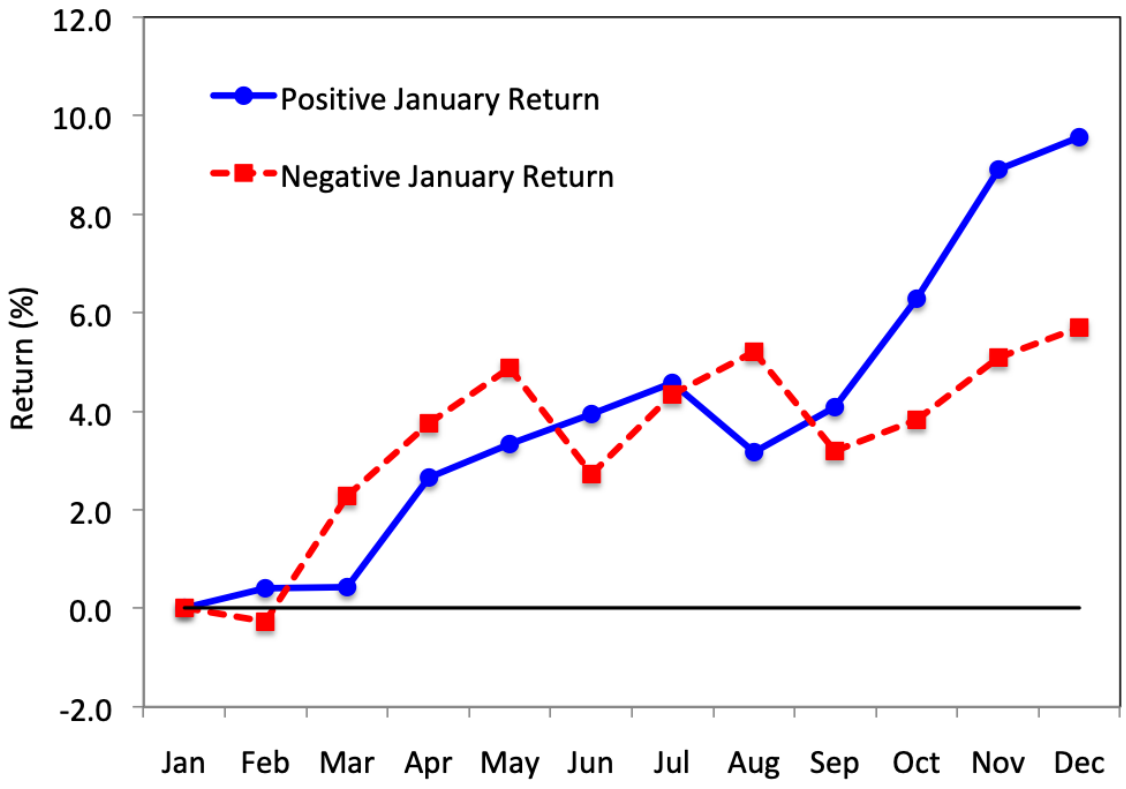

Figure 3.2: SPY average monthly returns (1993-2018)

3.3 NASDAQ 100 Index (NDX)

The NASDAQ 100 Index includes the 100 largest domestic and international companies listed on the NASDAQ stock market based on market capitalization. It reflects companies across major industry groups including computer hardware and software, telecommunications, retail/wholesale trade and biotechnology, but does not contain securities of financial companies. Table 3.9 shows a comparison of NDX's ROY returns for years with positive and negative January returns since 1986. During the past 33 years, there have been 22 positive-January signals and 11 negative-January signals. When the Index was up in January, it registered a positive ROY return 77% of the time, compared to 64% for years with a down January. The average ROY return following an up January was an impressive 16.5%, more than twice the average return in other years, whereas the median ROY return for years with an up January was lower than its down-January counterpart.

	Positive January Return	Negative January Return
Mean Return (%)	16.5	7.4
Median Return (%)	8.2	10.7
Mean Positive Return (%)	24.7	26.8
Mean Negative Return (%)	−11.4	−26.5
Number of Years	22	11
Percent Positive	77	64

Table 3.9: NDX ROY returns (1986-2018)

The large difference between the average ROY performance figures is due to larger and more frequent ROY losses in down years following a down January, as shown by a comparison of the mean negative ROY returns in Table 3.9. The average negative ROY return for years with a down January was more than twice its corresponding value for years following an up January, while the average positive returns were about the same in the two cases.

Table 3.10 summarizes a comparison of NDX's ROY returns for years with positive or negative January returns in excess of 4%. Since 1988, there have been a total of 15 years in which January was either up (10 occurrences) or down (5 occurrences) by more than 4%. While the difference in success rate between $4\%+$ up/down January signals is about the same as that reported earlier in Table 3.9 for any up/down January, the gap in average ROY returns following extreme January signals was much wider than the corresponding result for any up/down January. The average ROY return following a $4\%+$ up January was more than six times its down-January counterpart, with the mean positive return larger by more than a factor of two. Overall, extreme January gains affected primarily the magnitude of ROY gains, with no significant effect on the success rate, while extreme January losses did not exhibit any predictive significance.

The short-term predictive capability of NDX's January return is examined in Tables 3.11 and 3.12. Neither the average February return nor the success rate show any correlation with NDX's

	$> 4\%$ January Gain	$> 4\%$ January Loss
Mean Return (%)	18.6	2.9
Median Return (%)	9.7	8.3
Mean Positive Return (%)	34.3	16.4
Mean Negative Return (%)	-18.1	-17.5
Number of Years	10	5
Percent Positive	70	60

Table 3.10: NDX ROY returns following $4\%+$ January gains/losses (1986-2018)

	Positive January Return	Negative January Return
Mean Return (%)	0.7	1.5
Median Return (%)	2.2	2.7
Mean Positive Return (%)	5.6	6.9
Mean Negative Return (%)	-5.8	-5.1
Number of Years	23	11
Percent Positive	57	55

Table 3.11: NDX February returns (1986-2018)

January return regardless of its magnitude. The statistics presented in these tables indicate that NDX's January performance does not have any predictive capability as far as the short-term performance of the Index is concerned.

The heavily-traded QQQ is an ETF established in 1999 based on the NASDAQ-100 index. To examine any seasonal trends associated with the January Barometer, QQQ's performance since

	$> 4\%$ January Gain	$> 4\%$ January Loss
Mean Return (%)	-0.5	0.0
Median Return (%)	2.2	-0.6
Mean Positive Return (%)	6.9	3.7
Mean Negative Return (%)	-9.3	-2.5
Number of Years	11	5
Percent Positive	55	40

Table 3.12: NDX February returns following $4\%+$ January gains/losses (1986-2018)

	Positive January Return	Negative January Return
Mean Return (%)	9.1	-3.5
Median Return (%)	7.6	10.6
Mean Positive Return (%)	20.0	22.8
Mean Negative Return (%)	-16.2	-35.2
Number of Years	10	9
Percent Positive	80	67

Table 3.13: QQQ ROY returns (2000-2018)

inception is analyzed in Tables 3.13-3.14. Table 3.13 presents the ROY returns for years with positive and negative January returns, while Table 3.14 shows the corresponding February returns. There has been an equal number of positive and negative January signals in the 18 full years QQQ has been trading. A positive January signal for QQQ has led to a much better mean ROY return and a 20% higher success rate. On the other hand, neither the average February return nor the

	Positive January Return	Negative January Return
Mean Return (%)	-1.1	1.1
Median Return (%)	0.3	-1.4
Mean Positive Return (%)	3.4	8.9
Mean Negative Return (%)	-6.5	-5.1
Number of Years	11	9
Percent Positive	64	44

Table 3.14: QQQ February returns (2000-2018)

short-term success rate show any correlation with QQQ's January return. Hence, QQQ's January performance is not a good indicator of QQQ's short term returns. These results for QQQ are qualitatively similar to the statistics presented earlier for its underlying index.

The average monthly returns of NDX for the remaining months of up-January and down-January years are shown in Figure 3.3. It is clear from this figure that with the exception of the summer months, the sign of NDX's average monthly return throughout the year is independent of NDX's January return. The average monthly returns in the July-October period appear to correlate with NDX's January return in that on average, the Index advances strongly during the summer following a positive January signal, but loses significant ground during the same period following a down January. Digging deeper into each year's price action, we find that the success rates for a summer rally in NDX have been 73% and 45% for the positive and negative January signals, respectively. These results suggest that unlike earlier results for February and ROY returns, NDX's January return may be a good indicator of the Index's summer performance.

3.4 Russell 2000 Index (RUT)

The Russell 2000 index includes approximately 2000 small-cap companies, and serves as a benchmark for small-cap stocks in the U.S., much like the S&P 500 index is used to benchmark

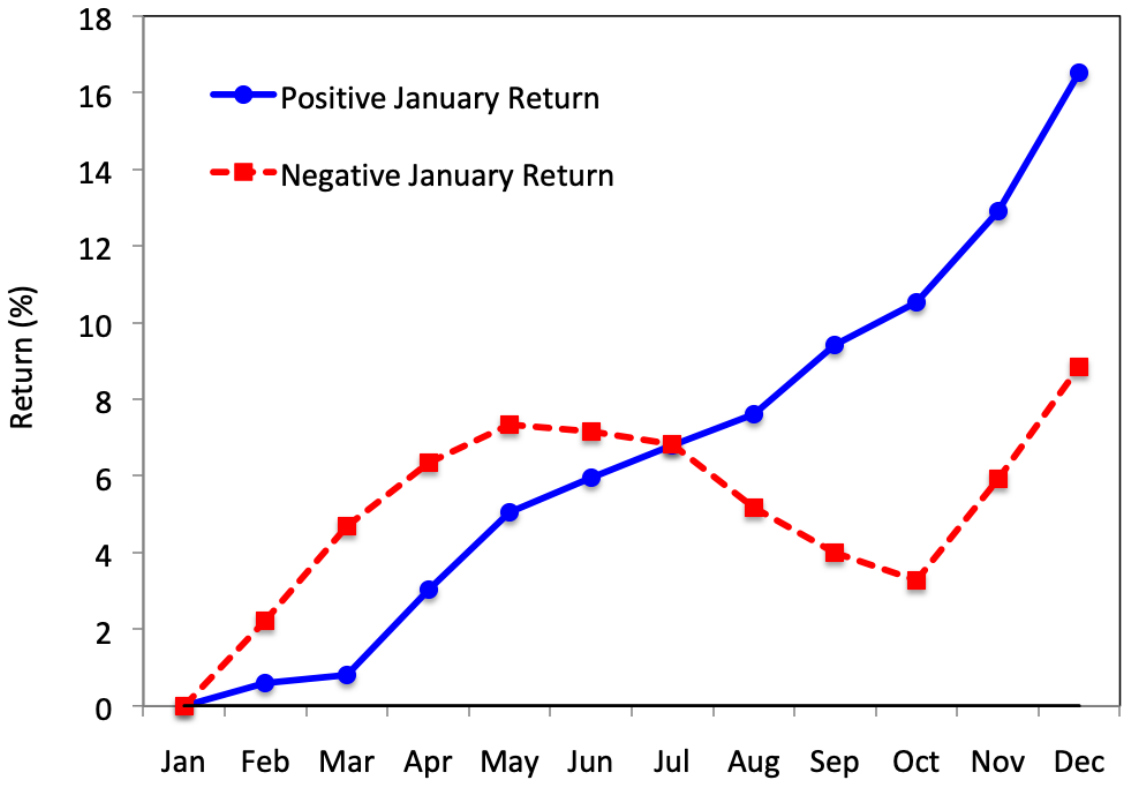

Figure 3.3: NDX average monthly returns 1986-2018

large capitalization stocks. Mutual fund investors favor the RUT because it reflects the investment opportunity presented by the entire market rather than opportunities offered by narrower indices which may contain more stock-specific risk. Hence, it is of interest to examine if any seasonal tendencies associated with the RUT are captured by the January Barometer.

A comparison of RUT's ROY returns for years with positive and negative January returns is presented in Table 3.15 for the period $1987 - 2018$. During that time, there have been 16 positive-January signals and 15 negative-January signals. January is believed to be a period of outperformance by small-cap stocks (cf. the January Effect) so it is a bit surprising to find an equal split in the number of positive and negative signals. When the RUT was up in January, it registered a positive ROY return 75% of the time, compared to 53% for years with a down January. The average ROY returns following positive and negative signals are about the same (both around

	Positive January Return	Negative January Return
Mean Return (%)	9.8	8.9
Median Return (%)	10.8	6.5
Mean Positive Return (%)	15.4	26.2
Mean Negative Return (%)	−7.2	−10.9
Number of Years	16	15
Percent Positive	75	53

Table 3.15: RUT ROY returns (1987-2018)

$9-10\%$), though the median ROY return for years with an up January is about 70% higher than its down-January counterpart. The main difference between the statistics for the two signals is the much higher success rate following a positive January. However, a negative return in January has not been a reliable indicator of weak ROY returns. In fact, RUT's largest ever ROY return (of about 50%) was achieved following a down January in 2003.

The reliability of the January Barometer for RUT improves if the signal is triggered by an extreme January return of at least 4% (positive or negative). The statistics for RUT's ROY return following positive or negative January returns in excess of 4% are shown in Table 3.16. Since 1987, the extreme signal has been triggered 14 times; 9 years with positive January returns of $4\%+$ and 5 years with negative January returns of at least 4%. The success rate for a $4\%+$ up January signal increases to about 90% from 75% reported earlier in Table 3.15 for any up January. In addition, a wide gap develops in average ROY returns following extreme up and down January signals, in contrast to virtually no distinction reported in Table 3.15 between the positive and negative signals for any up/down January. Specifically, the average ROY return following a $4\%+$ up January was nearly twice as large as its down-January counterpart. Overall, a positive January return of at least 4% in RUT appears to have been a very good indicator of the Index's ROY return, though the sample size is still small and a larger number of signals will be needed to further establish the

	$> 4\%$ January Gain	$> 4\%$ January Loss
Mean Return (%)	13.2	7.3
Median Return (%)	9.4	7.9
Mean Positive Return (%)	15.3	26.7
Mean Negative Return (%)	-3.9	-21.9
Number of Years	9	5
Percent Positive	89	60

Table 3.16: RUT ROY returns following $4\%+$ January gains/losses (1987-2018)

reliability of this indicator. Similar to the results for any down January, a negative January return in excess of 4% does not exhibit any significance as an indicator for weak ROY returns. The second largest ROY return (of about 41%) in RUT was achieved in 2009 following a 10% down January!

As shown by the statistics in Table 3.17 for RUT's Februray returns since 1987, the sign of RUT's January return does not have any predictive significance as far as the short-term performance of the Index is concerned. On the other hand, when only extreme January returns in the Index are considered to trigger a signal, the January Barometer shows more promise as an indicator of short-term performance. Table 3.18 summarizes the statistics for RUT's February returns following $4\%+$ moves in January. When RUT has been up at least 4% in January, it has continued to advance in February about 80% of the time, to score an impressive monthly return of 2.2% on average. In contrast, a $4\%+$ negative return in January has been followed by a further decline in February 60% of the time, with an average February loss of 2.3%. These results suggest that an extreme $4\%+$ RUT return in January could potentially be a reliable indicator of RUT's short-term performance, though this hypothesis is based on small sample sizes of 9 and 5 for extreme positive and negative signals, respectively, and must be tested with additional observations.

The iShares Russell 2000 IWM ETF was established in 2000 to replicate the investment results of RUT. It is the largest small-cap ETF and the second most actively traded ETF in the world.

	Positive January Return	Negative January Return
Mean Return (%)	0.5	2.2
Median Return (%)	0.5	3.0
Mean Positive Return (%)	3.8	5.6
Mean Negative Return (%)	−3.2	−4.4
Number of Years	17	15
Percent Positive	53	67

Table 3.17: RUT February returns (1987-2018)

	$> 4\%$ January Gain	$> 4\%$ January Loss
Mean Return (%)	2.2	−2.3
Median Return (%)	1.0	−0.1
Mean Positive Return (%)	3.9	2.3
Mean Negative Return (%)	−3.5	−5.4
Number of Years	9	5
Percent Positive	78	40

Table 3.18: RUT February returns following $4\%+$ January gains/losses (1987-2018)

Statistics for IWM's performance since inception are presented in Tables 3.19-3.22. Tables 3.19 and 3.20 present the ROY returns for years with positive and negative January returns, while Tables 3.21 and 3.22 show the corresponding February returns. These statistics for IWM are qualitatively similar to those presented earlier for its underlying index. However, the strength of the positive signal associated with a $4\%+$ January return is diminished for ROY returns, and enhanced

	Positive January Return	Negative January Return
Mean Return (%)	5.6	10.5
Median Return (%)	7.3	7.0
Mean Positive Return (%)	13.6	27.5
Mean Negative Return (%)	−7.7	−15.0
Number of Years	8	10
Percent Positive	63	60

Table 3.19: IWM ROY returns (2001-2018)

	$> 4\%$ January Gain	$> 4\%$ January Loss
Mean Return (%)	10.2	12.0
Median Return (%)	7.9	19.2
Mean Positive Return (%)	13.8	26.3
Mean Negative Return (%)	−4.5	−30.6
Number of Years	5	4
Percent Positive	80	75

Table 3.20: IWM ROY returns following $4\%+$ January gains/losses (2001-2018)

for the corresponding February returns. In particular, the success rate for ROY returns following a $4\%+$ January is reduced to 80% (from 89% for 33 years of RUT data), while the success rate for the corresponding February returns is increased to 83% (from 78% for the RUT data). Similarly, the success rate of the negative $4\%+$ signal in predicting a down February has grown to 75% for IWM, compared to 60% for longer-term RUT data. These results suggest that the significance

of large January moves in RUT as an indicator of short-term performance has persisted (or even improved) following introduction of the IWM ETF.

	Positive January Return	Negative January Return
Mean Return (%)	0.1	0.1
Median Return (%)	1.0	0.7
Mean Positive Return (%)	2.0	4.5
Mean Negative Return (%)	−3.7	−4.3
Number of Years	9	10
Percent Positive	67	50

Table 3.21: IWM February returns (2001-2018)

	$> 4\%$ January Gain	$> 4\%$ January Loss
Mean Return (%)	0.6	−3.7
Median Return (%)	1.0	−1.6
Mean Positive Return (%)	2.0	1.6
Mean Negative Return (%)	−6.7	−5.1
Number of Years	6	4
Percent Positive	83	25

Table 3.22: IWM February returns following $4\%+$ January gains/losses (2001-2018)

Finally, the difference between average RUT returns in the remaining months of up-January and down-January years is presented in Figure 3.4. It is clear from this figure that with the exception

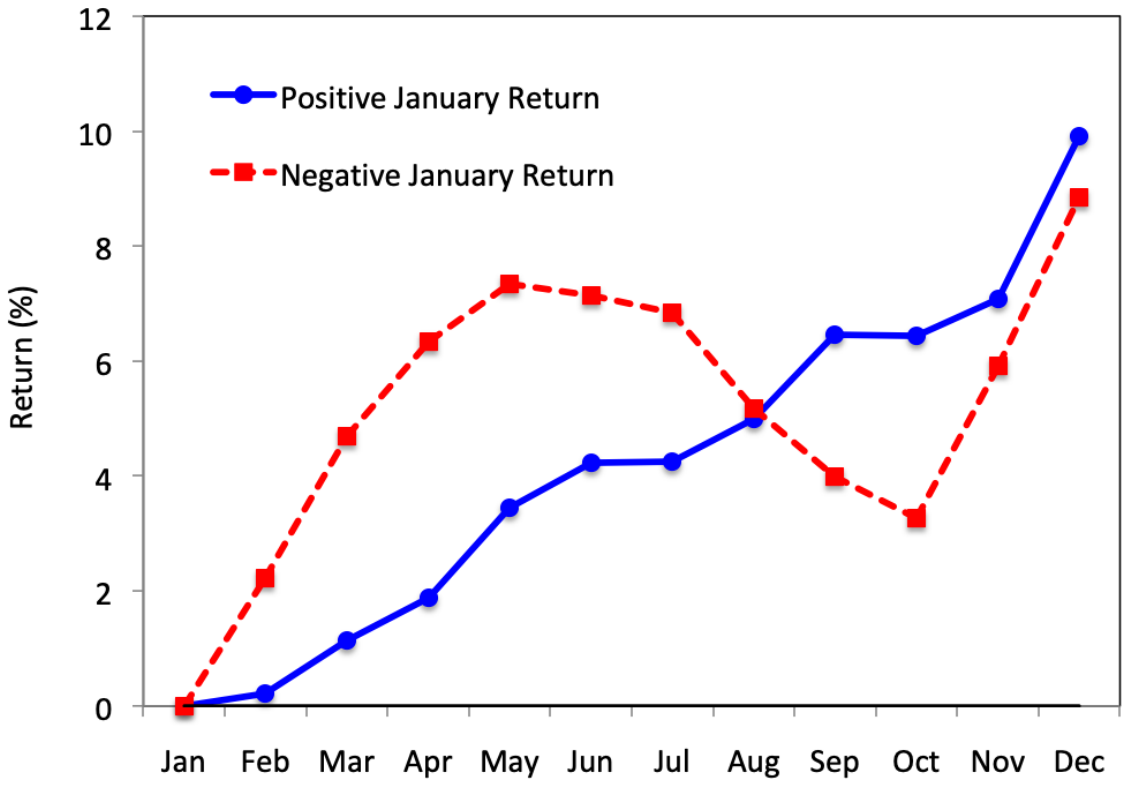

Figure 3.4: RUT average monthly returns (1987-2018)

of the summer months, the sign of RUT's average monthly return throughout the year has been independent of RUT's January return during the past 32 years. The average monthly returns in the July-October period appear to correlate with RUT's January return, i.e. the Index moves higher (on average) during the summer following a positive January signal, while it suffers a substantial decline (on average) during the same period following a down January. The success rates for a summer rally in RUT have been 75% for the positive January signal and 47% for the negative January signal. These observations are similar to those described earlier for the NASDAQ 100 index. Hence, it appears that RUT's January return is a better indicator of its summer performance than its February or ROY returns.

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