THE JANUARY BAROMETER: FACT OR FICTION?

by

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ABSTRACT

The January Barometer is a theory that claims 'As goes January, so goes the year'. Proponents claim that if the stock market rises in January, the year will follow suit. Conversely, if the market falls in January it will end the year lower. This study uses linear regression analysis to determine if January has any greater predictive value of the following 12-month returns than the other eleven months. It tests two stock market indices over four different time periods. The results of the study provided little evidence to show that January, or any of the other months, can predict the direction or magnitude of stock market returns for the coming twelve months.

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TABLE OF CONTENTS

1. INTRODUCTION

The Efficient Markets Hypothesis (EMH) is one of the most extensively researched topics in financial economics; see Fama (1965, 1991). The EMH claims that current security prices fully reflect all available information. If the EMH were correct then any out-performing of the market would be coincidence rather than skill on the part of the investor.

Despite strong evidence that the stock markets are efficient, there have been many studies documenting calendar anomalies, for example, Thaler (1987 a, b). It is accepted that there are historical anomalies, but can investors take advantage of them to earn superior returns in the future?

While many interesting market anomalies have been studied, this paper will focus on the 'January Barometer', which claims 'as goes January, so goes the year'. This phenomenon has been widely documented in the press, particularly at the beginning of each year, but not so widely studied in a formal setting. This study will look at the whether January returns can predict the direction of the market in the following twelve months, and if so, is it more reliable than the other eleven months? In other words, as goes the month, how goes the next twelve months?

2. LITERATURE REVIEW

2.1 Efficient Market Hypothesis and the Random Walk Theory

"I'd be a bum in the street with a tin cup if the markets were efficient." Warren Buffett

The Efficient Market Hypothesis is a controversial and often disputed theory. Eugene Fama (1965) argued that there are many knowledgeable investors actively competing in the market at any point in time, and that prices at that time reflect all information on past events as well as future events. This means that in an efficient market the current price of a security will be a close estimate of its value.

It follows that if all available information is known then any change in stock price will be in response to new information. If it were new information then it would have been unpredictable and therefore stock prices must move unpredictably. A random walk is that price changes must be random and unpredictable - that movement in stock prices will not follow any pattern or trend and that past movements cannot be used to predict future movements.

There are three forms of the Efficient Market Hypothesis. The 'weak-form hypothesis' says that prices reflect all information, including price history, trading volume and short interests. This form of the EMH implies that if the information available points to a potential change in price, all investors would know about it and would exploit the information, and therefore result in a price change.

The 'semi strong-form hypothesis' asserts that all available information, including the fundamental data on the company, is reflected in stock prices. Again, any information would be available to all investors and the stock price would move accordingly.

The 'strong-form hypothesis' states that prices reflect all available information, as well as information available only to insiders. While no one would argue that insiders have information that is not available to the public, there are many rules and regulations to control the use of inside information.

2.2 Technical Analysis

Technical Analysis is the search for recurring or predictable patterns in price movements, and would fall under the weak form of the EMH. This means that the analysts use past information to forecast future events. Technical Analysts may recognize the value of the current information on a company but they believe it is not necessary for successful trading strategies. Followers of the efficient market theory believe that technical analysis is without merit. Any information that was available in the past is reflected in the current stock prices and abnormal returns are not consistently possible.

2.3 Stock Market Anomalies

Market anomalies are patterns of past market movements that can be used to outperform passive investment strategies. Theoretically, if an anomaly were discovered, the benefit would soon disappear because investors would move to exploit it and drive the price of the security up, thereby eliminating the anomaly.

Anomalies are often the result of data mining. Statisticians say that if you torture data long enough, it will confess to anything. The rapid evolution of computer technology has allowed analysts access to a vast amount of data. Researchers then sort through the data looking for strategies to outperform the market. It is acknowledged that some anomalies do in fact exist, however, it is questionable whether they will pay off. The data used may be over the very long term and quite different results come from shorter-term studies or from different time periods. There are further issues such as transaction costs that may affect the results of trading based on an anomaly.

2.4 The January Barometer

As mentioned, it is acknowledged that there are market anomalies that seem to contradict the Efficient Market Hypothesis. If this is true, the investor must be quick to take advantage of them before they disappear. There are several well-known market-timing theories that continue to come up over time. One of the most well known is the January Effect. Historically, stocks in general, and small stocks in particular, generate higher returns in the month of January. This is an intriguing theory that does not seem to disappear in spite of the fact that it is well known and well publicized. January is historically the best month to be invested in stocks in markets around the world.

One of the most popular explanations for the January Effect is tax loss selling in December and after year-end the prices go back up to equilibrium. However, the January Effect has been documented in countries where December 31 is not the tax year-end. There is an argument that US investors affect worldwide markets and the December 31 tax year-end in the US can create the January Effect even in countries that do not have December 31 as their year end.

Another theory is that the January Effect is the result of investing new money from year-end bonuses or profit-sharing plans. Behavioural theorists take the position that January is a new year and investors start with renewed optimism and a clean slate.

The January Barometer is another market anomaly that may be closely related to the January Effect. This theory claims that 'as goes January, so goes the year'. Yale Hirsch, founder of the annual 'Stock Trader's Almanac', is credited with coining the term 'January Barometer'. He claims that if the S&P 500 moves higher in January then the year will follow suit, while if the index declines in January, the market will end the year lower. Mr. Hirsch believes that this phenomenon is reasonable because the new congressional session convenes in January and sets the mood and direction of the economy. Further, the President gives his State of the Union address and presents the annual fiscal budget, setting national goals and priorities.

In a Wall Street Journal article written by John R. Dorfman (1987), Mark Hulbert, editor of the Hulbert Financial Digest, said that this phenomenon is not surprising because odds are that any given January will show gains and so will any given year. Further, Gerald Perritt, editor of the Investment Horizons newsletter, said that no matter what happens in January, if you said the market would be up in the next eleven months, you would be correct 72.5% of the time.

In the same article, Richard Arms, VP, Eppler Guerin Turner Inc., investment banker, noted that January is part of the total performance of the year and the prediction is just a self-fulfilling prophecy. He suggested that a trend, once begun, tends to remain in motion until something derails it. Eugene Peroni, director of technical research for Janney Montgomery Scott Inc., stated that even if the January market movement predicts the direction of the market for the year, it does not predict the magnitude of the yearly performance. Mr. Peroni said that the indicator is a curiosity much like the groundhog theory or the theory that women's hemlines predict the market.

Sam Stovall, Business Week Online (2004), believes that the January Barometer has some merit. He feels that investors look at January as a fresh start, that the reasons to be nervous vanish with the dawn of the new investment calendar. Mr. Stovall notes that if January can predict the direction of the market, can it predict which industries to invest in? He tested a 'frozen' portfolio consisting of ten industries from the S&P 500 with the best performance from the prior month. He found that all months were barometers for the following twelve months over the period from 1970 – 2003, but that January had the highest average out-performance. He notes that September had a better record for choosing the industry out-performance, and that May and December had a better record for market out-performance.

Critics of the January Barometer claim that it is only relevant to analyze January's predictive power in relation to the next eleven months, not the twelve months that include January. This is true in that if the strategy includes the full year an investor cannot implement it because the month is over when the necessary information is available to act on.

The Hirsch Organization continues with the yearly study of the January Barometer. In the Stock Trader's Almanac (2005) they have included the eleven-month, twelve-month and calendar year's accuracy of January's predicting ability. They have included not only the results for the S&P 500 since 1938, but for the Dow Jones Industrial Average (DJIA) since 1938, and the NASDAQ since 1971. The results show that January has the highest predictive value for all time frames and in all indices except the calendar year on the NASDAQ. It seems that April has higher predictive ability and September has the same percentage of accuracy as January in that index.

The January Barometer did not have a consistent track record prior to 1934. Yale Hirsch, Stock Traders Almanac (2005), believes the reason for this is the 'Lame Duck' Amendment to the US Constitution in 1933. Hirsch's theory is that before 1934, Congress convened in December and the newly elected representatives and senators who were elected in November did not actually take office until December of the following year. The congressmen who were defeated stayed in office for the following year and were known as 'lame ducks'.

In 1933 the Twentieth or 'Lame Duck' Amendment was ratified and members elected to congress in November took their official positions in January of the following year. The President's inauguration day was also moved to January. Hirsch observes that these are events that greatly affect the US economy and the course of the stock market. He believes if these events were changed to a different month the January Barometer would lose its effectiveness.

Russell Fuller (1978) looks at the January Barometer and the 5-Day Index, which uses the changes in the market in the first five trading days of the year to forecast the direction of the market. His study found that looking at both the DJIA and the S&P500, the January Barometer correctly forecasted full year results 26 out of 32 years, or 81%, compared to 25 times for the 5-Day Index, or 78%.

Fuller expanded his study to include markets prior to World War II. Using the DJIA in the years from 1929 to 1977 (49 years), the January Barometer was successful 37 times compared to the 5 Day Index at 35 times. Going back to 1898 (80 years), the January Barometer won 57 times (71%) and the 5-Day Index 53 times (66%).

Using the S&P 500 as the market index the score is tied at 37 times for the years 1929 to 1977 (49 years). Fuller shows that the January Barometer is just slightly better at forecasting full year results than the 5-Day Index.

Fuller went on to determine which market index to use in testing the January Barometer and the 5-Day Index. He found that in three years out of the past 47 the 5-Day Index gave opposite signals when using the DJIA or the S&P500. For the January Barometer there were four years of conflicting signals, depending on which index you used.

In analyzing his results, Fuller states that while the January Barometer results seem impressive, if you simply said at the beginning of each year that the market (DJIA) would be up at the end of the year, you would have been right 21 of the 32 years, or 66% of the time. Going back even further, of the 80 years since 1898 the market was up 49 times, or 61%.

Fuller goes on to point out that, in forecasting full year results based on either of the theories does not help in putting together a trading strategy. If the investor waits for the results of the first week or month of the year before buying or selling, he will have to use the prices available, that is, he can not go back to the beginning of the year to begin the trading strategy. Therefore, when studying the January Barometer and the 5-Day Index you should only look at what happens after either the first 5 days or after the end of January, depending on which theory you are following. When using these new parameters, the 5-Day Index actually improves it's predicting ability to 26 of the 32 years on the DJIA, or 81%, while the January Barometer's ability falls to 24 times or 75%. When looking at the full 80-year period the 5-day Index has a 64% success rate the

January Barometer 63%. This is not much better than the 61% success of predicting each year that the market will go up.

Fuller then looks at just the best years of predicting the DJIA performance, which is the period 1946 to 1977 using the 5-Day Index, and measures the success rate of the sell signal. His thought was that if an investor sold his long position (or shorts the position if the previous year had been a sell signal) when the first five days of the year were down, and invested in a 4% yielding asset for the year, what would the success ratio be?

Using the signal of the 5-Day Index an investor would have gained about 7.7% per year, or an average of 2% per year more than the DJIA without dividends. When adjusting for dividends the average return for an investor just using the DJIA index would have been 9.7%, and the investor using the 5-Day Index would have made 10.4%. Fuller then adjusted for transaction costs, which reduced the 10.4% return to 9.6%.
Fuller concludes that, while these anomalies hold true in some years, over a longer time period an investor would have been better off buying and holding the index.

Brown and Luo (2004) begin their study by acknowledging that the January Barometer is related to the January Effect. They confirm that the January Effect does exist. They use data from the New York Stock Exchange for the period 1941 to 2002. The authors not only confirm that the January Effect exists, but that when the market goes up in January it goes up more than the other calendar months, and when the market goes down, it has the smallest average loss. They conclude from this that January is certainly the best month to be in the market and the January Effect exists.

The authors then study the January Barometer by testing whether acting on the sign of January's return is any better than acting on the sign of any of the other calendar month's returns, for the purpose of predicting returns. They test three distinct theories when looking at this phenomenon.

The first theory is 'As goes the month, how goes the year?'. Here they define 'year' as the twelve-month period including the calendar month in question. In other words, it includes the returns of the month being studied. The results of the study show that during the time period the returns in January successfully predict the sign of the twelve-month period 72.1% of the time. They also found that December had the same success rate.

Brown and Luo then tested the theory 'as goes the month, how goes the rest of the year?'. They define 'the rest of the year' as the eleven months following the calendar month in question. The results show that when January is positive, the eleven months following show a mean and median return ranking eighth and fourth, and a Sharpe Ratio ranking fifth against the other month's predictive values. There were more positive results for January's predictive value when January had a negative return. Bear markets in Januaries showed the lowest mean return, lowest median return, and lowest Sharpe Ratio of any of the months. Brown and Luo explain that the eleven months following January is the only time frame that does not include January returns and therefore benefit from the January Effect.

Finally, Brown and Luo test 'as goes the month, how goes the next twelve months?'. The 'next twelve months' in this case is the full year after the calendar month in question. This means that all of the time periods being studied will include the January Effect. The results of this test show that January's returns successfully predict the direction of the stock market 67.2% of the time, again tied with December as having the highest percentage of correct predictions.

The authors show that January's predictive value is even stronger when the one-month movement is down rather than up. The market has worse performance over the following twelve months if January has a bear market than any other 'bear months'. Brown and Luo conclude that January clearly has predictive value for the next twelve months and that it is better than the predictive value of any of the other twelve months.

Bloch and Pupp (1983) test two variations of the January Barometer, January Predictive Hypothesis (JPH), over the period 1950 – 1982. The first variation, JPH-1, tests if the directional change in the S&P500 for the month of January will predict what the market will do over the calendar year. The second variation, JPH –2, tests whether a change in January predicts the direction of the change in the following twelve-month period – that is, to the end of January of the following year. Both tests ask if the change in the market in January is a predictor of market movement and if so, is it any better than any of the other eleven months.

Bloch and Pupp assert that it is not enough to just check the direction of the market in January and then at the end of the period. They note that if a statistical series moves in one direction for an extended period, any given month should be an accurate predictor of future movements in the index. They give the example of the Consumer Price Index. The CPI has gone up each year. Given that, it would not be surprising if any month predicts the change for the year. They felt that more sensitive and sophisticated statistical techniques would be needed and decided to carry out a regression analysis to test their theory.

The independent variables are the same in each of the two models. The first is the natural log of the ratio of successive end-of-the-month values of the S&P500 Index for each of the twelve months of the year. The model had twelve equations and the monthly ratios were introduced sequentially.

The second independent variable was the square of the first variable, which tested for non-linear effects. The third variable is the natural log of a time trend to eliminate distortions caused by secular changes in the market.

The dependent variable for JPH-1 is the natural log of the January 1 to December 31 ratio in the S&P500. The results, using the independent variables described above, showed that January, April, May, June, September and November are positive and statistically significant at the 5% level, indicating that these six months can forecast the change in the market for the year, with January, September and November being the best predictors.

However, September and November are of little use to investors as the year is almost over. The squared variable was not significant, showing that non-linear effects did not influence the model. Rho was small and not significant, indicating that there was no autocorrelation. The R-squares were high, January's being the highest at .536. The coefficient in January was third highest and the t-stat of 4.238 was larger than any other month, giving strong support that the movement in the market in January is useful in predicting yearly changes in the stock market. However, five other months also support the January Predictive Hypothesis as well.

JPH-2 uses the same independent variables but the dependent variable is the natural log of the ratio of the S&P500 index for the full twelve months following the month of the independent variable. Using this model no month has a coefficient that is statistically significant. January has the highest t-statistic at 1.805 but it is not statistically significant and questions the validity of JPH-2.

The authors note that the relationships are very sensitive to small changes in data due to the small number of observations. A year in which the January performance and yearly performance were highly correlated could change the result of the study. Bloch and Pupp conclude that, once the built in correlation is removed neither the change in January nor any other month is significantly related to movement in the market for the following twelve months.

3. METHOD

One of the purposes of testing an anomaly is to create a trading strategy for investors to act on and earn higher returns than they would if they had invested in the market index. As Fuller (1978) points out, it is clear that testing the year, including the January returns, is not a strategy that can be implemented by an investor, so the results are not relevant for this purpose. Brown and Luo (2004) identify that using only the eleven months after January excludes the very month that produces the highest returns (January). Therefore, the test should be on the predictive value of January (and the other months) on the market returns of the following twelve months.

Bloch and Pupp (1983) found evidence of January having predictive value in the period 1950 to 1982, when looking at the following eleven months, or the balance of the year. When they looked at the twelve-month period, they found that January had greater predictive value than the other months but not at a 5% significance level. This finding is also consistent with Fuller (1978), and yet the January Barometer continues to be discussed in the press year after year. Brown and Luo (2004) concluded that January did predict the direction of the market.

This study looks at whether any month's returns can consistently predict what the market will do in the following twelve months through four different time periods from 1926 to 2003. Of particular interest is whether January has any greater predictive value than the other eleven months.

The study looks at two market indices through the period – the S&P500 with dividends, a value-weighted index, and the Center for Research in Security Prices Equal Weighted Common Stock Index with dividends (CRSP-EW). The S&P500 index was used in the Bloch and Pupp (1983) study. It is a broad US value-weighted index and is likely the most commonly referenced U.S. equity benchmark. It consists of more than 70% of the total market capitalization of all stocks traded in the U.S. The CRSP-EW index is a broad equal-weighted index containing historical market data on more than 20,000 stocks from the NYSE, AMEX and NASDAQ markets.

Linear regression analysis, using the ordinary least squares method, was used to test each index for the periods 1926 to 2003, 1926 to 1949, 1950 to 1982, and 1983 to 2003. The independent variable (**x**) is the predicting month's return, and the dependent variable (**y**) is the return for the one year starting with the month following the predicting month.

The regression equation is:

$$\mathbf{y}_{m+1} = \mathbf{a} + \mathbf{b}\mathbf{x}_m + \mathbf{e}$$

where $\mathbf{x}_m$ is the monthly return in month m, $\mathbf{y}_{m+1}$ is the annual return for the year starting in month m + 1 and **e** is the error term.

After sorting the data into months and then into time periods, the first regression was run using monthly returns on all of the Januarys from 1926 to 2003 as the **x** variable, and the annual returns of February 1 of the same year to January 31 of the following year as the **y** variable. Regressions were run in the same way for all of the months, and then for all of the months in each of the other three time periods.

4. RESULTS

The regression results are listed in Tables 6.1 to 6.4 (pages 20 to 23). The tables report the **x** (slope) coefficient with the corresponding t-statistic, the intercept with the corresponding t-statistic, and the R-square for each of the months in each time period. Of particular interest in this study is the significance of the **x** coefficient t-statistic, which is the ratio of the coefficient to its standard error. At the 5% level, the only statistically significant result for January was in the period 1950 to 1982. This held true for both the S&P500 and the CRSP- EW indices. No other month showed significant results in that time period. Bloch & Pupp (1983) found that during the same time period that January had the highest predictive value for the following twelve months, although not at the 5% level.

In further reviewing the results in the tables, the full period from 1926 to 2003 reveals that both indices have statistically significant results for the **x** coefficient for the month of February, indicating that that month had predictive value during the time period. The CRSP – EW index also had statistically significant results for April, July and August in the same period.

For the period 1926 to 1949 February again shows a statistically significant t-statistic for the S&P500 index. The CRSP – EW index shows a significant t-statistic for February, as well as July and August. One might begin to conclude that perhaps February has the more predictive value than January, however, February did not show any predictive value for the periods 1950 to 1982 and 1983 to 2003.

The final time period, 1983 to 2003, showed that no month predicted the returns in the coming year in either the S&P500 index or the CRSP-EW index.

5. CONCLUSION

This study has found little support for the January Barometer. Using the S&P500 and the CRSP – EW indices, the only time period where the results showed that January had predictive value was from 1950 to 1982, the same period studied by Bloch and Pupp (1983). Interestingly, February showed evidence of (negative) predictive capability for both indices for the period 1926 to 2003, and for the period 1926 to 1949. There was no indication that the same held true for the periods 1950 to 1982, and 1983 to 2003. Using the CRSP – EW index the months of April, July and August also showed significant results for the full period (1926 to 2003), and July and August for the period 1926 to 1949.

It should be brought to the reader's attention that there are very few observations in the shorter time periods. For the period 1926 to 1949 there are only 24 observations, 1950 to 1982 has 33 observations and 1983 to 2003 has 21 observations. Adding, removing or changing just one year makes a significant difference to the results. The full period has 78 observations and can be considered more reliable than the other periods. There was still no evidence that January had any predictive value in that time period.

In summary, this study concurs with the findings of Fuller (1978) and Bloch and Pupp (1983) in that January's returns cannot be used as a reliable indicator for a trading strategy and adherents to the Efficient Market Hypothesis can continue to rest easy.

6.1 CRSP-EW Index 1926 to 2003 and 1926 to 1949

Results for the regressions of 12-month returns on monthly returns

The regression is of the form $\mathbf{y_{m+1} = a + bx_m + e}$, where x is monthly return in month m, and y is the annual return for the year starting in month m + 1. The t-statistics for slope coefficients significant at the 5% level are highlighted.

	1926 to 2003			1926 to 1949		
Month	**X Co-ef** **t-stat** *(77df)*	**Intercept** **t-stat**	**R-Sq**	**X Co-ef** **t-Stat** *(23df)*	**Intercept** **t-stat**	**R-Sq**
January	0.12 0.23	0.17 3.31	0.00	-1.11 -0.83	0.27 1.99	0.03
February	-2.21 -2.69	0.21 4.91	0.09	-4.66 -2.61	0.27 2.40	0.24
March	-0.84 -1.19	0.20 4.38	0.02	-0.53 -0.37	0.24 1.81	0.01
April	1.20 2.91	0.16 4.59	0.10	1.23 1.73	0.20 2.08	0.12
May	-0.49 -0.91	0.20 3.93	0.01	-0.68 -0.68	0.28 1.80	0.02
June	0.33 0.39	0.20 3.37	0.00	0.04 0.02	0.27 1.44	0.00
July	1.93 4.09	0.14 3.90	0.18	2.58 3.26	0.11 1.13	0.33
August	1.00 3.03	0.15 4.99	0.11	1.57 3.73	0.11 1.82	0.39
September	0.02 0.04	0.17 5.30	0.00	0.23 0.40	0.17 2.46	0.01
October	-0.12 -0.28	0.17 5.36	0.00	0.13 0.16	0.17 2.39	0.00
November	0.47 0.91	0.16 4.90	0.01	0.15 0.15	0.18 2.23	0.00
December	0.45 0.64	0.17 4.78	0.01	1.07 0.82	0.20 2.26	0.03

6.2 CRSP-EW Index 1950 to 1982 and 1983 to 2003

Results for the regressions of 12-month returns on monthly returns

The regression is of the form $y_{m+1} = a + bx_m + e$, where x is monthly return in month m, and y is the annual return for the year starting in month m + 1. The t-statistics for slope coefficients significant at the 5% level are highlighted.

	1950 to 1982			1983 to 2003		
Month	**X Co-ef** **t-stat** *(32 df)*	**Intercept** **t-stat**	**R-Sq**	**X Co-ef** **t-stat** *(20 df)*	**Intercept** **t-stat**	**R-Sq**
January	1.30 2.63	0.10 2.19	0.18	-0.05 -0.05	0.16 1.98	0.00
February	0.65 0.63	0.17 4.06	0.01	-0.70 -0.67	0.17 2.83	0.02
March	-1.12 -1.24	0.19 4.54	0.05	-1.48 -1.01	0.18 2.96	0.05
April	1.01 1.22	0.17 3.88	0.05	1.34 1.51	0.12 2.80	0.11
May	0.33 0.34	0.19 4.02	0.00	0.71 0.98	0.11 2.94	0.05
June	1.16 1.13	0.20 4.13	0.04	-0.60 -0.67	0.13 3.93	0.02
July	0.84 0.81	0.17 3.50	0.02	-0.87 -1.17	0.12 3.57	0.07
August	-0.28 -0.29	0.19 4.04	0.00	-1.02 -1.48	0.13 3.24	0.10
September	-0.30 -0.31	0.18 3.95	0.00	-1.18 -1.14	0.13 2.56	0.06
October	-0.99 -1.31	0.18 4.19	0.05	0.25 0.34	0.15 2.82	0.01
November	0.82 0.97	0.16 3.24	0.03	0.75 0.95	0.13 2.94	0.05
December	0.19 0.19	0.18 3.49	0.00	-1.70 -1.02	0.17 3.18	0.05

6.3 S&P500 Index 1926 to 2003 and 1926 to 1949

Results for the regressions of 12-month returns on monthly returns

The regression is of the form $y_{m+1} = \mathbf{a} + \mathbf{b}\mathbf{x}_m + \mathbf{e}$, where x is monthly return in month m, and y is the annual return for the year starting in month m + 1. The t-statistics for slope coefficients significant at the 5% level are highlighted.

	1926 to 2003			1926 to 1949		
Month	**X Co-ef** **t-stat** ***(77df)***	**Intercept** **t-stat**	**R-Sq**	**X Co-ef** **t-Stat** ***(23df)***	**Intercept** **t-stat**	**R-Sq**
January	0.07 0.14	0.12 4.93	0.00	-2.10 -1.56	0.14 2.25	0.10
February	-1.50 -2.54	0.13 5.40	0.08	-3.33 -3.29	0.13 2.29	0.33
March	-0.62 -1.17	0.14 4.96	0.02	-0.28 -0.28	0.13 1.72	0.00
April	0.60 1.72	0.12 4.89	0.04	0.55 0.94	0.12 1.85	0.04
May	-0.42 -0.85	0.14 4.76	0.01	-0.68 -0.74	0.15 1.80	0.02
June	-0.55 -0.96	0.14 4.50	0.01	-0.82 -0.75	0.17 1.79	0.02
July	0.70 1.81	0.11 4.47	0.04	1.17 1.91	0.07 1.17	0.14
August	0.34 0.93	0.12 4.94	0.01	0.87 1.44	0.07 1.26	0.09
September	0.67 1.75	0.13 5.57	0.04	1.06 1.92	0.12 2.51	0.14
October	0.20 0.56	0.12 5.56	0.00	0.14 0.20	0.10 0.05	0.00
November	0.59 1.38	0.11 4.88	0.02	0.77 0.91	0.11 2.00	0.04
December	0.82 1.32	0.11 4.30	0.02	2.16 1.91	0.08 1.56	0.14

6.4 S&P500 Index 1950 to 1982 and 1983 to 2003

Results for the regressions of 12-month returns on monthly returns

The regression is of the form $\mathbf{y_{m+1} = a + bx_m + e}$, where x is monthly return in month m, and y is the annual return for the year starting in month m + 1. The t-statistics for slope coefficients significant at the 5% level are highlighted.

	1950 to 1982			1983 to 2003		
Month	**X Co-ef** **t-stat *(32 df)***	**Intercept** **t-stat**	**R-Sq**	**X Co-ef** **t-stat *(20 df)***	**Intercept** **t-stat**	**R-Sq**
January	1.21 2.43	0.11 4.23	0.16	0.14 0.18	0.14 3.47	0.00
February	0.23 0.23	0.12 4.47	0.00	1.41 1.72	0.13 3.90	0.13
March	-1.32 -1.47	0.14 4.72	0.07	-1.72 -1.69	0.17 4.21	0.13
April	0.72 1.05	0.11 3.89	0.03	0.84 0.91	0.12 3.27	0.04
May	-0.32 -0.39	0.12 4.41	0.00	1.22 1.31	0.11 2.99	0.08
June	-0.48 -0.54	0.13 4.09	0.01	0.66 0.60	0.13 3.52	0.02
July	0.23 0.29	0.12 3.72	0.00	-0.84 -0.89	0.14 3.58	0.04
August	0.39 0.55	0.12 4.07	0.01	-0.80 -1.07	0.14 3.42	0.06
September	-0.73 -0.91	0.13 3.88	0.03	0.77 0.84	0.15 3.44	0.04
October	0.16 0.26	0.12 4.05	0.00	0.24 0.42	0.13 3.80	0.01
November	0.71 0.98	0.11 2.97	0.03	0.04 0.05	0.14 3.69	0.00
December	-0.12 -0.12	0.13 3.47	0.00	-0.64 -0.63	0.15 3.45	0.02

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