Seasonal Stock Returns: Insight Provided Through a Reproduction of Haugen and Jorion 1996

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Abstract

In our study, we reproduced discoveries Haugen and Jorion (1966) made with their paper "The January Effect: Still There After All These Years." The paper argued persuasively for the existence of a so-called "January" anomaly in returns for small market cap stocks up until 1993. Moreover, the persistence of such an effect is a point of interest. Our reproduction uses financial data from 2000 to the present in 2012 and gives evidence for the presence of the January effect. Furthermore, the findings show there are no signs of the arbitrage opportunity dissipating anytime in the near future. After thorough statistical analysis, we discuss modern trends in behavioral psychology and economics to explain our secondary finding that the effect of the anomaly has lessened greatly in recent times since Haugen and Jorion's study, but that it can still be expected to persist into the future.

Introduction

The efficient market hypothesis (Fama 1965), influential to many investors, is a generally accepted theory that states that financial markets are "informationally efficient," and assumes that stock prices reflect the available information at any given time. As a result, investors should not be able to achieve above-average returns without taking on above-average risk. Despite this theory, however, there have been several documented examples of anomalous behavior in security markets in recent decades based on consistent seasonal patterns. Examples of such a phenomenon include the Monday effect, the Halloween effect, and the January effect.

The Monday effect refers to the findings that the average return on Monday tends to be lower than that of the rest of the week (French 1980; Gibbons and Hess 1981; Damodaran 1989). Perhaps the newest reported anomaly, the Halloween effect, addresses the findings that average returns between May and October are significantly lower than those between November and April (Bouman and Jacobsen 2002).

The January effect describes one of the most well-known market anomalies, in which during the first ten trading days in January, stocks with small market capitalization tend to produce greater returns. This effect is commonly explained by tax-loss selling. In other words, there is a rebound in stock prices following the year-end pressure on individual shareholders to sell underperforming stocks so as to claim a capital loss on their taxes.

This effect, first noted in a study by Wachtel (1942), was brought to the attention of the modern finance world by Rozeff and Kinney (1976). As this anomaly is exploitable, and that the market is reasonably efficient, it would seem that over the years this effect would be priced away and would ultimately disappear. However, a recent study by Haugen and Jorion (1996) found that the effect continues to exist with no decrease in magnitude. The question then remains: if the January effect is so easily exploited, does it still have an influence on modern day market trends?

In our project, we will attempt to determine if the January effect does in fact still exists within the most recent decade. In order to determine this, we will attempt to reproduce the study of Haugen and Jorion (1996) using monthly average returns from the S&P 500 taken during the years 2000-2012. We will then propose possible explanations of our findings, discuss the implications of these results in terms of the theory of efficient markets, as well as examine likely explanations behind the effect. Lastly, we will suggest possible further research.

Methodology

Our data consists of monthly statistics for the top 1000 stocks from January 2000 to the present (April 28, 2012). We filtered the list to only include stocks that had IPO-ed before or on January 2000 and were actively traded on the New York Stock Exchange over the time period for the last dozen years or so. We used total market capitalization in the middle of the time period (rankings as of 2006) to allow for growth and shifts in rankings over this time. And finally, we eliminated stocks that did not have complete statistical data from the Quantmod package. This is in contrast to Haugen and Jorion's study which ranked stocks by market capitalization at the beginning of the time period. We partitioned the stocks into deciles and ran regressions corresponding to each decile before performing our analysis. Within each decile, the following regression was run over the full time period:

$$r_{j,t} = a_0 + a_4 J_t + e_{j,t}$$

where:

$r_{j,t}$ = monthly rate of return to decile j in month t

j_t = dummy variable taking a value of 1 if t is a January month and 0 otherwise

$e_{j,t}$ = unexplained component of the return to decile j in month t

Here, a_0 measures the average return for the decile for all months, and a_4 measures the difference between the average return for the decile in January and the average return for other months (variables chosen to match the Haugen and Jorion article).

Our hope was that with the deliberate choices to keep some aspects constant and to vary others, we would be able to reproduce the main findings of Haugen and Jorion's study done in 1996 while at the same time being able to infer shifting modern trends due to the slightly newer dataset.

Finally, within each decile we ran various regressions using different time-series analyses, which are listed in Table A below. These regressions are designed to measure the January effect, the interaction of the January effect with the time period since 1977 when the effect was again observed in the market, and the interaction of the January effect and the entirety of the time period of our sample.

Results

Table A: Regression analysis of NYSE data from 2000 to 2012: $r_{j,t} = a_0 + a_4J_t + e_{j,t}$

Decile	a_0	p-value (a_0)	a_4	p-value (a_4)
1	0.008326	3.55E-10*	0.02062	4.83E-06*
2	0.010808	1.35E-08*	0.01376	0.033*
3	0.011704	1.91E-13*	-0.01387	0.01*
4	0.011682	< 2E-16*	0.00641	0.148
5	0.014726	3.89E-13*	0.01166	0.0898
6	0.013491	< 2E-16*	0.00883	0.0335*
7	0.012226	3.44E-12*	0.00563	0.344
8	0.011008	< 2E-16*	-0.00411	0.322
9	0.014083	1.85E-14*	-0.01369	0.028*
10	0.019373	9.07E-10*	-0.00724	0.5
Total	0.012654	< 2E-16*	-0.01068	3.54E-08*

* *denotes significance at the 0.05 level*

Through our regression analysis, we verify the existence of the January effect still, but at a much smaller magnitude. There are some anomalies, in that there are negative values of a_4; perhaps we can take this to mean that traders are picking up on this cue in capturing this arbitrage opportunity.

In particular, we notice within the 1^{st} through 7^{th} deciles that the coefficient a_4 denoting the slope of the regressions decreases in magnitude – we take the interpretation of this “dummy” or indicator variable as the influence that January’s returns has on the stock’s return as a whole. The prevalence of positive values for lower value deciles, representing the smaller cap stocks in the NYSE, is promising for our study to support the existence of the January effect, even with modern financial data from 2000-2012, years after Haugen and Jorion did their study. We do note the negative a_4 value of -.014 for decile 3 – which ordinarily would be surprising since we expect the variable to be positive should January returns be higher and contribute positively to the overall returns- however because of the low p-value, we are able to use statistical significance to throw it out of the data mix to ascertain truer results.

And finally, our analysis for the relatively larger cap stocks, spanning deciles 8 through 10, reveals that overall the absolute value of the magnitude increases, which is consistent with our initial hypothesis. As market cap becomes even larger, we expect the January effect to be less present, so the trend toward more negative a_4 values representing the slope of the regression is consistent with the hypothesis that larger stocks would feel the effect of January returns to a lesser degree.

Conclusion and Discussion

Based our findings, we can conclude that the January effect still exists in the current markets, although the influence of the phenomenon has diminished in recent years.

While our results suggest that for the period from 2000-2012, the January effect is present, in this time period it exists at a smaller magnitude than measured in Haugen and Jorion (1996). As the scope of the January effect seems to have diminished slightly in recent years, it may suggest that as knowledge of this phenomenon spread, investors increasingly exploit the anomaly to capitalize on the anomalous behavior; thereby reducing the magnitude of effect and subsequently increasing the efficiency of the market. It is possible that in future years the January effect will disappear from the markets entirely.

Our results support the existence of the January effect from 2000 to 2012 in the New York Stock Exchange, but to a smaller degree than that found by Haugen and Jorion's in 1996. Thus, the evidence suggests that while the January effect may have decreased slightly since the last decade, it has since stabilized and remains readily exploitable by investors in the market. Now we seek to investigate the two explanations posited by Haugen and Jorion for our findings:

- The January effect is the result of market inefficiencies.

Opportunities for arbitrage disappear with time because the conditions necessary to capture such opportunities requires sufficient willingness to take on risk and agency problems such that the number of investors in the pool disappear.

- The January effect is not a result of the financial market being inefficient.

Without the opportunity for arbitrage and abnormal market returns, the inability for investors to capture such opportunities leaves the effect intact and able to persist over more years.

As mentioned, the January effect comes with high levels of risk; without enough investors willing to take on the risk, the arbitrage opportunity would still remain on the table without disappearing. As we identified in our study, the January effect has decreased in magnitude since 1996; various possible explanations may exist to explain this, but following the line of reason outlined above, one may be that investors are more and more willing to take on the risk of arbitrage.

Let's take a look at three possible theories explaining the phenomenon and then proceed to hypothesize why the magnitude has decreased over the past decade. Firstly, a common strategy for individual investors is to sell their stocks for tax reasons at the end of the year (to claim capital loss) and then reinvest in them after the first of January. A second studied reason is that year-end bonuses are often used to purchase stocks, which drives up their prices. A third reason is that internally, the January effect doesn't always happen - in the years of 1982, 1987, 1989, and 1990 of the month of January, small stocks underperformed large stocks. Thus, one possible reason the January effect has been decreasing in magnitude could be that in more recent years, there has been a trend for large cap stocks to outperform smaller stocks, but this is an issue for an entirely separate investigation altogether, which could be done at a future time.

In addition to the previously mentioned anomalous patterns in market behavior, further consistent trends in stock prices exist on a seasonal basis. These broad patterns are based in yearly tax dates, holidays, changes in the season, and possible seasonal psychological effects. Contrary to the efficient market hypothesis, these patterns tend to persist. Therefore it is important that further studies are conducted to gain a greater understanding of these trends. One possible area of research should examine the influence of behavioral finance in determining market anomalies and patterns. Studies in behavioral finance suggest that investors tend to act in certain ways, thus resulting in certain predictable patterns in the stock market. Krugman suggests that investors tend towards "trendy" stocks, which results in distorted stock prices and market inefficiency. As these market anomalies reflect issues in the theoretical model of asset pricing (CAPM), further important research should look to combine the findings on market anomalies with theories of behavioral finance in order to create improved asset-pricing models.

References

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* All data analysis performed through the software using R.

Appendix

```
# Stat 107
# Final Project R Code
# Jonathan Lee, Adam Chu, Eleanor Combs

library(quantmod)

# read csv/deciles
nyse <- read.csv("C:\\Documents and
Settings\\Administrator\\Desktop\\nyse.csv",header=FALSE,stringsA
sFactors=FALSE)
stocks <- nyse[,2]

sd1 <- stocks[1:100]
sd2 <- stocks[101:200]
sd3 <- stocks[201:300]
sd4 <- stocks[301:400]
sd5 <- stocks[401:500]
sd6 <- stocks[501:600]
sd7 <- stocks[601:700]
sd8 <- stocks[701:800]
sd9 <- stocks[801:900]
sd10 <- stocks[901:1000]

retd1 <- c()
jand1 <- c()

for (s in sd1) {
    x <- getSymbols(s,from="2000-01-01",auto.assign=FALSE)
    y <- monthlyReturn(x)
    retd1 <- c(retd1,y)
    for (i in 1:length(y)) {
     if (months(time(y[i])) == "January") {
          jand1 <- c(jand1,1)
     }
     else {
          jand1 <- c(jand1,0)
     }
    }
}

cat("1 done\n")

retd2 <- c()
jand2 <- c()

for (s in sd2) {
    x <- getSymbols(s,from="2000-01-01",auto.assign=FALSE)
```

```
     y <- monthlyReturn(x)
     retd2 <- c(retd2,y)
     for (i in 1:length(y)) {
      if (months(time(y[i])) == "January") {
            jand2 <- c(jand2,1)
      }
      else {
            jand2 <- c(jand2,0)
      }
     }
}

cat ("2 done")

retd3 <- c()
jand3 <- c()

for (s in sd3) {
     x <- getSymbols(s,from="2000-01-01",auto.assign=FALSE)
     y <- monthlyReturn(x)
     retd3 <- c(retd3,y)
     for (i in 1:length(y)) {
      if (months(time(y[i])) == "January") {
            jand3 <- c(jand3,1)
      }
      else {
            jand3 <- c(jand3,0)
      }
     }
}

cat("3 done")

retd4 <- c()
jand4 <- c()

for (s in sd4) {
     x <- getSymbols(s,from="2000-01-01",auto.assign=FALSE)
     y <- monthlyReturn(x)
     retd4 <- c(retd4,y)
     for (i in 1:length(y)) {
      if (months(time(y[i])) == "January") {
            jand4 <- c(jand4,1)
      }
      else {
            jand4 <- c(jand4,0)
      }
     }
}
```

```
cat("4 done\n")

retd5 <- c()
jand5 <- c()

for (s in sd5) {
    x <- getSymbols(s,from="2000-01-01",auto.assign=FALSE)
    y <- monthlyReturn(x)
    retd5 <- c(retd5,y)
    for (i in 1:length(y)) {
     if (months(time(y[i])) == "January") {
          jand5 <- c(jand5,1)
     }
     else {
          jand5 <- c(jand5,0)
     }
    }
}

cat("5 done\n")

retd6 <- c()
jand6 <- c()

for (s in sd6) {
    x <- getSymbols(s,from="2000-01-01",auto.assign=FALSE)
    y <- monthlyReturn(x)
    retd6 <- c(retd6,y)
    for (i in 1:length(y)) {
     if (months(time(y[i])) == "January") {
          jand6 <- c(jand6,1)
     }
     else {
          jand6 <- c(jand6,0)
     }
    }
}

cat("6 done\n")

retd7 <- c()
jand7 <- c()

for (s in sd7) {
    x <- getSymbols(s,from="2000-01-01",auto.assign=FALSE)
    y <- monthlyReturn(x)
    retd7 <- c(retd7,y)
    for (i in 1:length(y)) {
     if (months(time(y[i])) == "January") {
          jand7 <- c(jand7,1)
```

```
      }
      else {
            jand7 <- c(jand7,0)
      }
     }
}

cat("7 done\n")

retd8 <- c()
jand8 <- c()

for (s in sd8) {
     x <- getSymbols(s,from="2000-01-01",auto.assign=FALSE)
     y <- monthlyReturn(x)
     retd8 <- c(retd8,y)
     for (i in 1:length(y)) {
      if (months(time(y[i])) == "January") {
            jand8 <- c(jand8,1)
      }
      else {
            jand8 <- c(jand8,0)
      }
     }
}

cat("8 done\n")

retd9 <- c()
jand9 <- c()

for (s in sd9) {
     x <- getSymbols(s,from="2000-01-01",auto.assign=FALSE)
     y <- monthlyReturn(x)
     retd9 <- c(retd9,y)
     for (i in 1:length(y)) {
      if (months(time(y[i])) == "January") {
            jand9 <- c(jand9,1)
      }
      else {
            jand9 <- c(jand9,0)
      }
     }
}

cat("9 done\n")

retd10 <- c()
jand10 <- c()
```

```
for (s in sd10) {
    x <- getSymbols(s,from="2000-01-01",auto.assign=FALSE)
    y <- monthlyReturn(x)
    retd10 <- c(retd10,y)
    for (i in 1:length(y)) {
     if (months(time(y[i])) == "January") {
          jand10 <- c(jand10,1)
     }
     else {
          jand10 <- c(jand10,0)
     }
    }
}

cat("10 done\n")

rettot <-
c(retd1,retd2,retd3,retd4,retd5,retd6,retd7,retd8,retd9,retd10)
jantot <-
c(jand1,jand2,jand3,jand4,jand5,jand6,jand7,jand8,jand9,jand10)

reg1 <- lm(retd1~jand1)
reg2 <- lm(retd2~jand2)
reg3 <- lm(retd3~jand3)
reg4 <- lm(retd4~jand4)
reg5 <- lm(retd5~jand5)
reg6 <- lm(retd6~jand6)
reg7 <- lm(retd7~jand7)
reg8 <- lm(retd8~jand8)
reg9 <- lm(retd9~jand9)
reg10 <- lm(retd10~jand10)
regtot <- lm(rettot~jantot)

summary(reg1)
summary(reg2)
summary(reg3)
summary(reg4)
summary(reg5)
summary(reg6)
summary(reg7)
summary(reg8)
summary(reg9)
summary(reg10)
summary(regtot)
```