

ROBUST TEST OF THE JANUARY EFFECT IN STOCK MARKETS USING MARKOV – SWITCHING MODEL*

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Abstract

Using Markov-switching model, five return regimes are statistically determined for the monthly stock returns covering the period 1926 to 1992 and probabilistic inferences about these regimes are drawn. The results provide no support for the existence of the January effect. To account for the small-firm effect, again Markov-switching model is applied to ten portfolios sorted by market value deciles. We found a strong January effect for low capitalization stocks.

Keywords: Markov-switching Model; Regime shifts; January Effect

JEL classification: C12; C52; G14

Introduction

The traditional approaches use one January dummy variable or use eleven or twelve monthly dummy variables to estimate the January effect. These approaches assume two or several regime-shifts and impose an automatic switching mechanism triggered by a calendar date. If abnormal returns do not occur every January, it is a mistake to set the January dummy be the value one in every January. The January dummy regression creates an error-in-variables problem, which invalidates the statistical inferences. Furthermore, if the regime shift was caused by economic shocks rather than the calendar dates, a January dummy variable regression will wrongly attribute some of the non-seasonal regime shifts to seasonal dummies. This can lead to a spurious January effect. This paper uses a Markov-switching model to

estimate the regime shifts and to compare the return in January with other months. After the number of regimes is identified in this Markov-switching model, the model can estimate the transition probabilities from one regime to another regime. The regime shift probability is not zero or one as in the dummy variable regressions. Also, the Markov-switching model can designate each month to one of the regimes based on the inferential probabilities. Each January month may belong to a high or low mean return regime.

Stock Market Seasonality

The stock market seasonality, specially the anomalous January effect, has long been an interesting issue in empirical finance. (see Wachtel¹,). Quite a few researchers have documented the calendar anomaly of

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January effect in stock markets (Schwert², and Jones and Wilson³). Do stock return series really exhibit abnormal behavior in a particular month of a year? Or is it better characterized as the way Mark Twain says,

October-- This is one of the peculiarly dangerous months to speculate in stocks in. The others are July, January, September, April, November, May, March, June, December, August and February.

This paper investigates January effect in stock markets by applying a rigorous Markov-switching model.

Seasonality is defined as the cyclical behavior that occurs on a regular calendar basis. The easiest way to examine the seasonality is to plot the data. A simple plot of a monthly stock return series shows no regular pattern repeated over time. Intuitively, this is true since there is no obvious source of seasonal variation, such as the weather, summer vacation or holidays, etc., that can affect the stock market returns. Moreover, seasonality is not observable when it cannot be distinguished from other sources of fluctuation. This difficulty exists especially for those series with considerable fluctuations, such as stock returns. Using a graphic plot is definitely not a good approach and one needs a model of seasonal variations to provide a better answer.

A commonly used technique in the study of stock market seasonality is the regression analysis with dummy variables. Two types of dummy variable regressions are found in the literature: the regression with eleven monthly dummy variables and the regression with a single January dummy variable. To document the well-known January effect, the dummy variable regression has been applied by Keim⁴, Tinic and West⁵, Schultz⁶, Jones, Pearce and Wilson⁷ and Jones and Wilson³, Clark, McConnell and Singh⁸, among others. Despite the well-known problems of heteroskedasticity and autocorrelation of error terms, the dummy variable regression approach for analyzing the stock seasonality has never been questioned. This paper draws attention to some of the shortcomings of the traditional approaches and applies a robust method to examine the January effect in stock market returns.

Methodology Used

We use the equally weighted (EWR) monthly New York Stock Exchange (NYSE) index returns from the Center for Research in Security Prices (CRSP), and the corresponding decile portfolios $i=1,2,\dots,10$, covering the sample period January 1926 to December 1992.

Dummy Variable Regression

There are a wide variety of techniques for modeling the seasonal variations. Using eleven monthly dummies is one possibility. This approach is definitely not infallible. As Thomas and Wallis⁹ point out, a dummy variable regression will remove too much variation from the original series (in our case, the monthly stock return), attributing some of it incorrectly to variation in the seasonal dummy variables. Hence it is likely that the magnitude of the January effect resulting from the dummy variable regression is exaggerated. In addition to this fundamental criticism by Thomas and Wallis, a regression with eleven monthly dummies will not work well unless the pattern of seasonality remains constant over time. It is important to note that the seasonality is a deterministic component in a time series. If the seasonality pattern is indeed constant over time, then there are good reasons to expect the empirical results on the stock return seasonality to be more or less consistent.

Using the regression with just one January dummy to test the January effect has its own problems as well. First, this approach is not a model for seasonal variations. Since there are twelve months in a year, one monthly dummy cannot characterize the seasonal pattern of twelve months over a whole year. It is better to consider the January dummy regression as a two-regime model instead of a model for seasonality. In particular, it is a temporal regime shift model since the regime change is associated with a particular time of year. This regime shift interpretation seems to fit some financial economists' need; the model is simple (and perhaps robust, see discussion below) and it appears to provide useful information about whether January's mean return is higher than the average mean return for all months other than January.

To model a time series characterized by regime shift, there are alternatives besides the dummy variable regressions. Before we present an alternative, we demonstrate that the January dummy regression is a very restricted regime shift model in that it implicitly assumes a two-regime shift and imposes an automatic switching mechanism from one regime to another triggered by a calendar date, January. In other words, the number of regimes is known and the regime shifts are certain and observable. To be more specific, these models assume that there are exactly two regimes, which is very restrictive -- Simplicity is its chief merit. Moreover, a recent celebrated

result by Andrews¹⁰ shows that a test of parameter shift based on the explicit alternative of two regimes still has nontrivial power against a wide range of other alternatives, including the alternative of more than two regimes. For example, suppose that the time series is subject to a regime shift every January and August (a three-regime model), a regression with only one January dummy (a two-regime model) is capable of revealing the January regime (but certainly not the August regime). Hence it can be a useful model for studying the January anomaly provided one does not question the assumption of the regime shifts being certain and observable. The most disputable restriction of the January dummy regression lies in the assumption of a certain and observable regime shift, i.e., a higher return automatically occurs in every January. In terms of the literature of regime shift, this amounts to the study of regime shift with the change points being known. Furthermore, regime shift triggered by the January is a very specialized model of regime shift. The consequence is that, if there were a regime shift caused by economic shocks rather than the calendar dates, a January dummy variable regression will wrongly attribute some of the non-seasonal regime shifts to seasonal dummies. This can lead to a spurious January effect.

Thus, both traditional approaches, the regression with eleven dummy variables and the regression with a single January dummy may, given their limitations, not be the best or appropriate for studying the January effect. In search of a better model, one is led to consider a new model from the study of the seasonal variation or the regime shift. Since it is generally very difficult to model seasonality (see Davidson and MacKinnon¹¹ for further discussions) and there is no compelling reason to model the seasonality of stock returns, the chance of gaining from modeling stock returns with unsure seasonality should be very rare. On the other hand, it is convincing to note that the stock return series is subject to regime shifts rather than seasonal variations. This is particularly true for a univariate time series with a long sample period, which has a higher probability of regime shift. Therefore, it seems natural to start with a model of regime shift.

Prelude

Regime Shifts and Markov-switching Model

To make sure that a model of regime shift is relevant, we apply the Lagrange Multiplier (LM) test of Andrews¹⁰ to detect parameter instability. When the LM test is

applied to the equally weighted monthly returns of stocks on the NYSE from 1926 to 1992, the statistic is 9.389 which leads to the rejection of the hypothesis of parameter constancy. In search a better regime shift model than the January dummy regression, we first review some existing regime shift models.

Two-regime models with permanent shift are well known in the econometrics and statistics literature, e.g., Goldfeld and Quandt¹² and Hinkley¹³, among others; for a recent application in empirical finance, (see Chou and DeGennaro¹⁴). This model is rather restrictive since it explicitly assumes only two regimes. The multiple regimes model with permanent shift appears more promising. The challenging task here is to identify multiple change points. Wichern, Miller and Hsu¹⁵ developed a methodology of estimating multiple change points. Haugen, Talmor and Torous¹⁶ applied this procedure to study Dow Jones Industrial Average (DJIA) volatility changes. However, the methodology developed by Wichern, et al. depends on some restrictive assumptions such as the normality and the first order autoregressive structure. A more serious problem is that, as Haugen, Talmor and Torous's simulations indicate that the method is imperfect as many change points are falsely identified. In general, econometricians and statisticians know very little about estimating multiple change points.

Another possibility is to consider a two-regime model with temporary shift. The temporary parameter shift can be pictured as a step function with one head and two shoulders. The most important aspect of this model is how to estimate the duration of the temporary regime. This type of modeling regime shift has been used by Hillmer and Yu¹⁷ in event studies. Hillmer and Yu's model is appropriate for high frequency data collected in a shorter sampling period; it is not suitable for our study.

The Markov-switching model, developed by Hamilton¹⁸, provides an attractive alternative to model a time series subject to regime shifts. It has had many fruitful applications in empirical macroeconomics (Hamilton¹⁸; Goodwin¹⁹), but has not been fully explored in empirical finance. The Markov-switching model is a multiple-regime model. It does not assume *a priori* the number of regimes, though Turner, Startz and Nelson²⁰ and Cecchetti, Lam, and Mark²¹ study stock markets using exactly two regimes in their Markov-switching models. The number of regimes is data dependent and can be estimated. Furthermore, the regime shift is dominated by

the Markov chain, a kind of stochastic process. More interestingly, the Markov-switching model permits optimal statistical inference about the estimated regimes. Specifically, this model derives the probability of the return of a given month belonging to a certain estimated regime. Thus, the Markov-switching model provides a statistical method of segmenting observed data into different regimes through this probabilistic inference. When the regime classification is done, we can examine the frequency distribution of January in high return regimes to discern the presence of January effect. This is similar to the methods of Hamilton and Goodwin, where Markov-switching models are used to date business cycles.

In the Markov-switching model, the path of time series data takes the form of a non-linear stationary process. In particular, the data is modeled as an autoregressive process with parameters subject to regime switching as determined by the outcome of a first-order Markov chain. Suppose the stock return follows a Markov-switching model. Then,

$$R_t - \mu_t = \phi_1 (R_{t-1} - \mu_{t-1}) + \phi_2 (R_{t-2} - \mu_{t-2}) + \dots + \phi_r (R_{t-r} - \mu_{t-r}) + \varepsilon_t \tag{1}$$

where, R_t is the stock return at time t and ε_t is assumed to be normally distributed with zero mean and finite variance σ^2 . The regime-dependent mean μ_t has its own dynamics, specified as a K-state first-order Markov chain.

$$\mu_t = \beta_{S_t} \tag{2}$$

where, S_t is an unobserved state variable at time t with values in a finite state space $S = \{1, 2, \dots, K\}$. Since elements of S are the possible regimes of the mean return, S_t represents the regime at time t . When the regime at time t is equal to j ($S_t = j$), the mean return at time t is equal to β_j , i.e. $\mu_t = \beta_j$.

Instead being a non-stochastic dummy variable, S_t is characterized by a first-order Markov chain,

$$\begin{aligned} \text{Prob}(S_t = j \mid S_{t-1} = i, S_{t-2} = k, \dots, R_{t-1}, R_{t-2}, \dots) \\ = \text{Prob}(S_t = j \mid S_{t-1} = i) = p_{ij} \text{ for } i, j = 1, 2, \dots, K. \end{aligned} \tag{3}$$

The sequence $\{S_0, S_1, S_2, \dots\}$ represents the historical regimes of the mean return that evolve according to the probability law shown above. One distinct property is that the conditional distribution of the next regime S_{t+1} , given the present regime S_t , must not depend on the distant past information set $\{S_{t-1}, S_{t-2}, \dots, R_{t-1}, R_{t-2}, \dots\}$. The transition probability, p_{ij} , is the probability of observing regime j at time t , given that the regime at time $t-1$ is equal to i . These probabilities characterize regime shifts of the time series data. The transition probabilities, p_{ij} form a $K \times K$ transition probability matrix, $P = [p_{ij}]$, with the constraint $\sum_{j=1}^K p_{ij} = 1, i \in S$. It is possible to extend the first order Markov chain to a higher order to allow for longer memory in the stock return regime shift. However, it involves enormous unknown parameters when large numbers of regimes are considered, as in this paper. Hence, we avoid this complication in this paper.

The first-order Markov-switching model is represented by the **Equations 1 through 3**. It contains two kinds of dynamics: the dynamics of the conditional mean, which is modeled by the autoregressive process; and the dynamics for the state variable S_t , which is modeled by the first-order Markov chain. The parameters in the Markov-switching model in **Equations 1 through 3** include the lag coefficients ϕ_1, ϕ_2, \dots , and ϕ_r , the mean returns for different regimes β_1, β_2, \dots , and β_K , the transition probabilities $p_{ij}, i, j = 1, 2, \dots, K$, and σ^2 . These unknown parameters can be estimated using the maximum likelihood method*. As a by-product, probabilistic inferences about the unobserved regimes can also be drawn via the “ r -lag smoother”. The r -lag smoother is the inferential probability of S_t given the observations up to time $t+r$, i.e. $P(S_t | t) = P(S_t | R_{t+r}, R_{t+r-1}, \dots) P(S | t)$. These estimation and inference procedures are derived from the basic filtering algorithm in Hamilton¹⁸.

The regression with the January dummy and the Markov-switching model share some similarities; they also differ in other respects. Both approaches are the *regime shift models and the regime shifts are temporal dependent*. In a two-regime case, the regime shift in the regression with the January dummy is determined by the calendar. The regime shift in the Markov-switching model is determined by the regimes in the consecutive periods. More specifically, the dummy variable regression can be

* We use the subroutine UMINF from the Fortran IMSL Library to perform the nonlinear optimization. The initial probabilities $P(S)$ are assumed to be unknown parameters. Those values are also estimated in optimization.

viewed as a special case of the Markov-switching model. The regression with a January dummy implies that $S_t = 1$ for January and $S_t = 2$ otherwise. In other words, $P(S_t = 1) = 1$ when in January and $P(S_t = 1) = 0$ otherwise. Hence, the regime switches are certain (non-stochastic) and exogenously determined by the calendar. In contrast, the Markov-switching model permits two possible regimes at each time t , both in January and non-January. Above all, regime switches are modeled by a stochastic Markov chain. Each regime in any given time period can shift to either regime in the next period. The characteristic of the regime shift is then endogenously determined by the observed data. As these differences suggest, the Markov-switching model is a more flexible model of regime shifts than is the dummy variable regression approach.

Market Returns

We begin the estimation with the NYSE, EWR market returns. We fit a variety of Markov-switching models with $r = 1$ to 3 lags and $K = 2$ to 7 regimes in the conditional mean equation. Among these 18 models, we pick the best model based on the Schwartz Information Criterion (SIC). Table 1 gives the SIC statistics for these models. It shows that the best model should have three lags and five or six regimes*. We use five regimes instead of six because of the parsimony. For this selected model, the estimated lag coefficients model are, $\phi_1 = 0.1177$, $\phi_2 = 0.1032$, and the estimated mean returns of each regime are $\beta_1 = 50.96$, $\beta_2 = 14.78$, $\beta_3 = 1.55$, $\beta_4 = -3.56$, and $\beta_5 = -19.09$. These five regimes will be referred as follows: (1) the positive outlier regime (the PO regime), (2) the bull regime, (3) the normal regime, (4) the bear regime, and (5) the negative outlier regime (the NO regime).

Table 2 displays the transition probability matrices, along with the estimated mean returns in parentheses. The number in the i th row and j th column in the table is the transition probability p_{ij} , which is the probability of observing regime j at time t , given that regime i is observed at time $t-1$. Note that the sum of each row is equal to one. This table shows that the estimated transition probabilities are consistent with the irreducible, persistent Markov chain. If the current regime is "normal", then there is a 99 per cent chance that the state in the next month will also be "normal" for the market returns. This

TABLE 1
THE SIC STATISTICS FOR DIFFERENT LAGS AND
REGIMES FOR EQUAL-WEIGHTED STOCK
RETURNS

Number of Regimes	Lags		
	AR(1)	AR(2)	AR(3)
2	9187.23	9181.45	9173.91
3	9065.3	9045.11	9041.22
4	8958.23	8952.22	8940.23
5	8933.02	8921.38	8902.74
6	8925.53	8968.55	8902.85
7	8984.78	8976.28	8962.26

indicates that regime shifts occur only in response to surprising discrete events. For the positive outlier regime, the chance to stay in the same regime next month is 42 per cent. The chances to be in the bull, normal, and bear regimes in the next month are 12 per cent, 15 per cent and 22 per cent respectively. It is not surprising to see that the probability from a positive outlier to a negative outlier is zero. For the bull regime, it will most likely become the bear regime next month. The chance is 83 per cent. The chances of changing to a bull or a normal regime are much smaller, which are 8 per cent and 9 per cent respectively - - The chance from a bull regime to a positive outlier or a negative outlier is zero.

The transition probability for the bear regime is different from that of the bull regime. For the bear regime, it will never go back to the normal regime. Actually, 52 per cent of the time it will stay in the same bear regime and 20 per cent of the time it will be worse and will go to the negative outlier regime. For the negative outlier regime, only there is an 8 per cent of chances that it will be in the same state next month. Most likely, it will recover from the negative regime, with 49 per cent of chances of being back to the bear regime, 16 per cent back to normal, and 26 per cent for it go up to the bear regime. Comparing the bull and the bear regimes, we found that the patterns of changes are different in these two states. **The negative returns are usually followed by negative returns. However, positive returns are not usually followed by**

*In a Markov-switching model with multiple regimes, the number of parameters is typically large. We chose the SIC instead of the Akaike Information Criterion (AIC) for deciding on the best model because the SIC uses a heavier penalty factor for over-parameterization. If the AIC is used, the best model would have had three lags and seven regimes.

TABLE 2
TRANSITION PROBABILITY MATRICES FOR EQUAL-WEIGHTED STOCK RETURNS

		Regime at Time t				
		Positive Outlier (50.96)	Bull (14.78)	Normal (1.55)	Bear (-3.56)	Negative Outlier (-19.09)
Regime at time $t-1$	Positive Outlier	0.4219	0.2067	0.1511	0.2195	0.0007
	Bull	0.0001	0.0826	0.0876	0.8292	0.0006
	Normal	0	0	0.9913	0.0025	0.0062
	Bear	0.0453	0.2316	0	0.5242	0.1989
	Negative Outlier	0	0.2645	0.1632	0.4899	0.0823

Note: The mean returns of each regime are included in the parentheses.

positive returns. These are usually followed by negative returns. For the negative outlier regime, it will stay in the same regime with only 8 per cent of chances. It will recover and be back to the bear, normal, and bull regimes with probabilities of 49 per cent, 16 per cent and 26 per cent, respectively.

Significance and Impact of January and October Effect

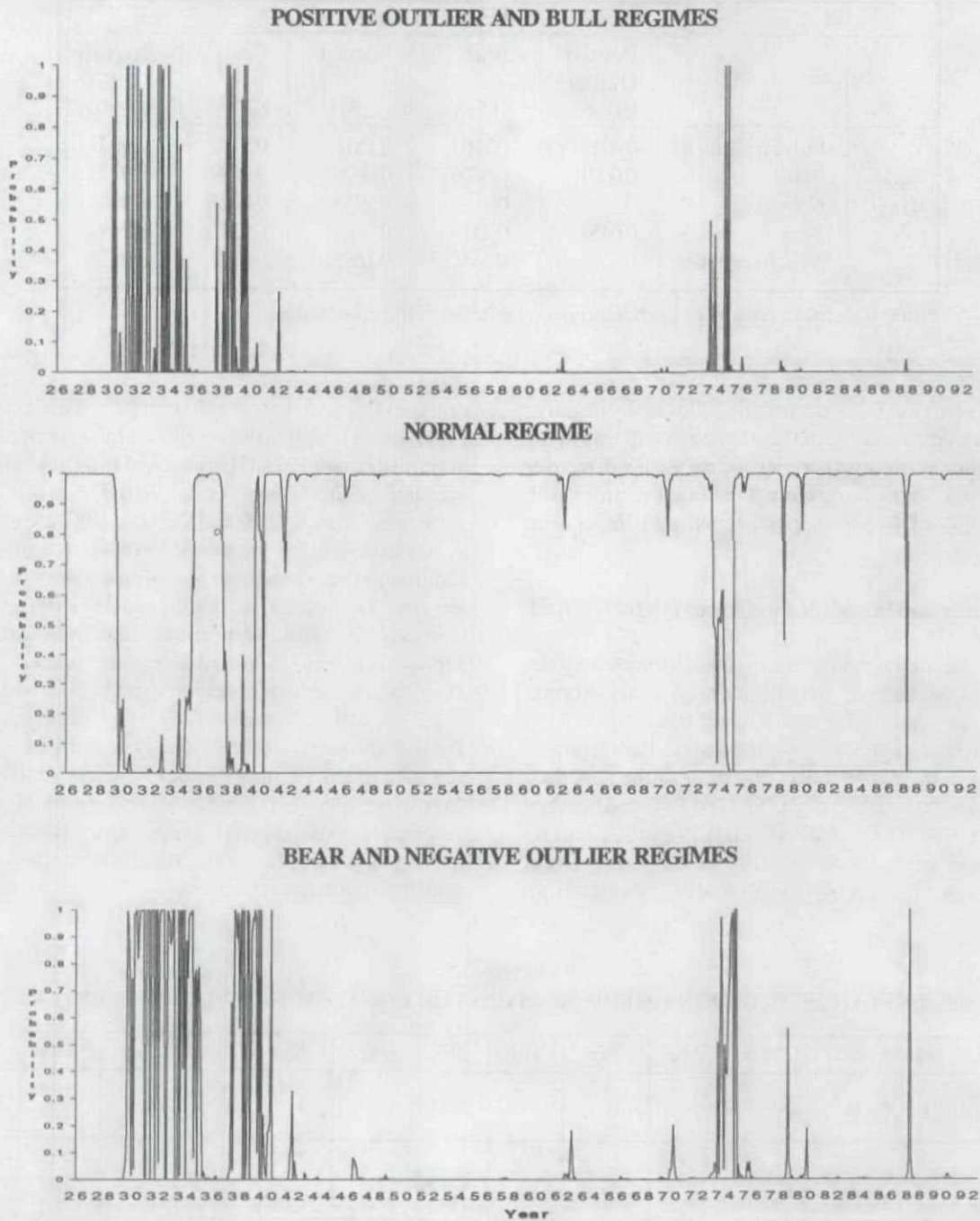
There are five different regimes identified by the Markov-switching model. In addition to the normal regime, we specify the positive and negative outliers, bull and bear regimes as well as abnormal regimes. Figure 1 in the paper shows that most of the abnormal regimes are observed between 1929 and 1942 and between 1972 and 1974. The period between 1929 and 1942 covers the period after the crash of 1929 and the Great Depression. This period is generally considered an

unusual period for stock market. The economy experienced a high inflation caused by oil price shocks during 1972 and 1974. The financial market seems to be affected by the oil shocks as well. The stock market crashes in October 1929 and October 1987 are identified as negative outliers by the Markov-switch model. In addition to these two months, Table 4 shows that there are four Octobers that belong to negative outliers. However, the table also shows that there are three September months identified as negative outliers as well. Therefore, we cannot conclude that October is the only "bad" month for investors. For the January effect, Table 4 shows five of the January months of sixty-six years are in bull regime. Besides January, we found that three of the July months are in the bull regime and one in the positive outlier regime. Comparing the frequencies of January and July, it is difficult to conclude a strong evidence of the January effect.

TABLE 3
FREQUENCY DISTRIBUTION OF FIVE REGIMES FOR EQUAL-WEIGHTED STOCK RETURNS

State	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Total
Positive Outlier	0	0	0	1	1	0	1	1	1	0	0	0	5
Bull	5	1	1	1	1	3	3	2	1	3	2	0	23
Normal	57	58	60	60	58	58	58	57	57	54	56	57	690
Bear	4	6	4	3	5	5	4	7	5	5	7	7	62
Negative Outlier	0	1	2	2	2	1	1	0	3	4	1	2	19

FIGURE 1
PROBABILITY OF REGIMES FOR EQUAL-WEIGHTED STOCK RETURNS



The upper graph displays the sum of the inferential probabilities in positive outlier and bull regimes; the middle one plots probability in the normal regime; the lower one is the sum of the probabilities in bear and negative outlier regimes. Note that the vertical sum of the probabilities in each month should be equal to one.

We have determined five possible regimes from the data set, $S_i = 1, 2, \dots, 5$. For any given month, the probability of this month falling within one of these regimes can be computed from the r -lag smoother $P(S_i | l)$. The graphs of these are shown in **Figure 1**. There are three graphs in **Figure 1**. These graphs show that the normal regime is the most important regime for most months, but not for all months. In particular, the normal regime dominates in the period after 1941.

A useful implication from these inferential probabilities is the classification of regimes. In each month, we can identify the regime which has the highest probability. Each month is then assigned to this unique regime. If a month is assigned to the regime j , then the inferential probability in the regime j is greater than the inferential probability of any other regime in this month, i.e., $P(S_i = j | l) > P(S_i = i | l)$ for all l and $i \neq j$. With this regime classification, each month's observed return is assigned to one of these five regimes. A detailed look at this regime allocation gives us information on the January effect. Notice that this regime classification does not depend on the calendar date like the January dummy variable regression. The regime classification in the Markov-switching model is data dependent and it shows the time series characteristics of each month's return.

The two outlier regimes, PO and NO, contain the "extreme" stock returns 50.96 per cent and -19.09 per cent, respectively. This indicates the existence of significant positive and negative "shocks." **Table 3** lists months assigned to PO and NO regimes and it shows 5 months are assigned to a PO regime and 19 months are assigned to a NO regime. Interestingly, the months assigned to the NO regime occurred during the Great Depression, European War, oil shocks in 1973 and 1978, and the 1987 stock market crash. It is also interesting to note that all of the PO regimes occurred before World War II. Since events like these arise randomly, it makes more sense to discuss the probabilistic inference for the bull, normal, and bear regimes only. Among those 19 months in the NO regime, four of those are in October, three are in September, and others in various months. It is difficult to conclude which month tends to be in the PO regime. Since there are only five months in PO regimes and these five months are different, we cannot relate the PO regime to the certain months of year.

Table 4 summarizes the number of observations assigned to PO, bull, normal, bear and NO regimes. The

TABLE 4
MONTHS ASSIGNED TO POSITIVE AND
NEGATIVE OUTLIER REGIMES

Year	Positive Outlier	Negative Outlier
1929		October
1930		June, September, December
1931		April, September, December
1932	July, August	April, May, October
1933	April, May	February
1934		July
1937		September
1938		March
1939	September	March
1940		May
1973		November
1978		October
1987		October

.....

details of the distribution of months in PO and NO regimes are already shown and discussed. For the rest of the three regimes, it shows the frequencies of different months in the normal regime are uniformly distributed among the twelve calendar months. The frequencies assigned to the bear regime are less uniformly distributed, but close enough. Inspecting the distribution of bull regimes, we find that the relative frequency of January (5 out of 23) is the highest. Compared to June, July, and October, each with three years in the bull regime, the bull regime observed in January is not statistically significantly higher than the other months to assert the presence of January effect.

January Size Effect

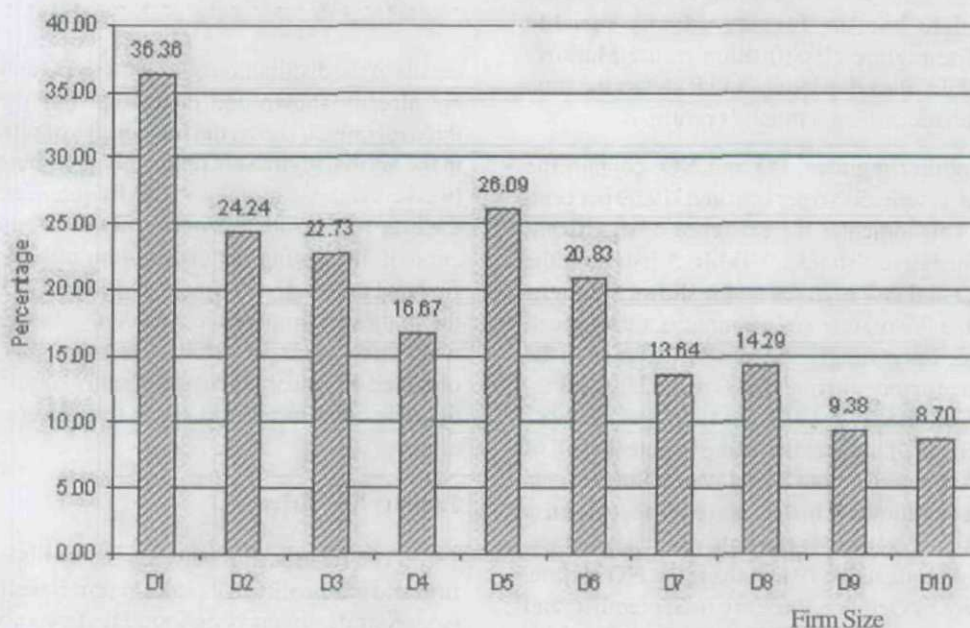
The relationship between the capitalization of the firm and seasonality in its stock return is well documented (see, Keim⁴). It has been found that average returns for small firms are substantially higher in January. Therefore, to further examine the January effect for different market value portfolios, ten portfolios with different capitalization are considered. These portfolios are denoted by D1, D2, ... and D10, where D1 contains the lowest and D10 contains the highest capitalized stocks. Markov-switching models with $r=1$ to 3 and $K=2$ to 7 are also

applied to each portfolio. We continue to use the SIC to determine the best model for each portfolio. The orders of auto regression for the best models are: AR(1) for D1, D2, D4, and D10; AR(2) for D5; AR(3) for D3, D6, D7, and D9. For the number of regimes, all ten portfolios yield 5 regimes except for D2 (7 regimes) and D3 (6 regimes).

After computing the r-lag smoother, the same regime classification criterion is used to match months with regimes* Summary results highlighting the January effect are shown in Figures 2 and 3. Figure 2 displays the percentage of the bull regime that occurred in January against firm size. The percentage of bull regimes that occurred in January is calculated as the ratio of the total number of Januaries classified in the bull regimes to the

total number of months classified in this regime. This figure shows that the percentage of abnormal returns occurring in January does not decrease monotonically with the firm size. Nevertheless, the percentage of abnormal returns occurring in January is more prominent for the smaller than the larger firms. To illustrate this further, Figure 3 examines the frequency distributions in the bull regime for each of the ten portfolios. The vertical axis in each graph is the number of months assigned to the bull regime. For the low capitalization portfolios (D1-D2), the January effect is evident. On the other hand, for D7-D10, there is no evidence of January effect. The medium capitalization portfolios (D3-D6) present a "gray" area, with a higher frequency occurring in January than in other months.

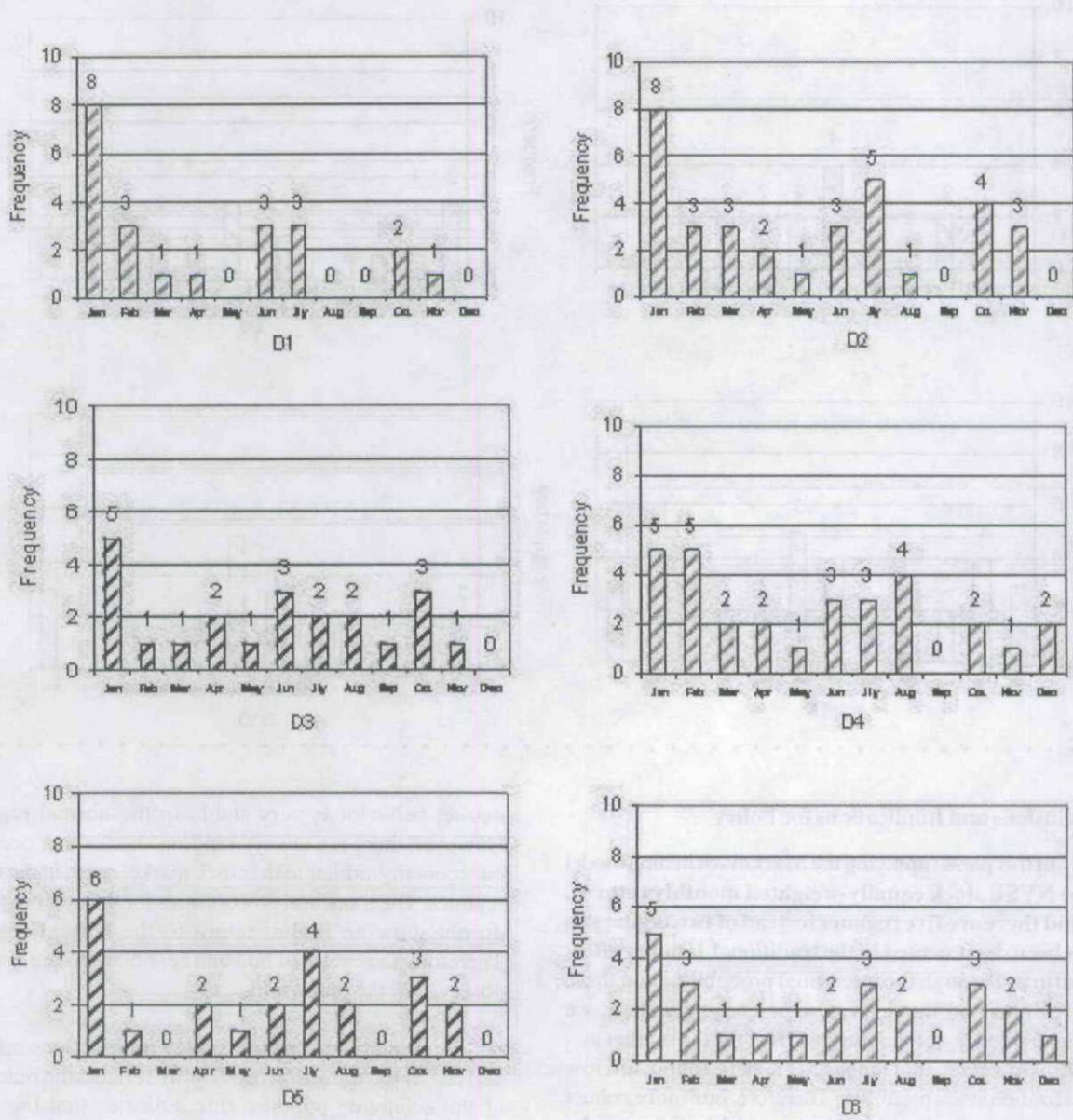
FIGURE 2
THE PERCENTAGE OF THE BULL REGIME IN JANUARY



D1 is the portfolio with lowest capitalization and D10 is the one with the highest capitalization. The height of this bar graph is the percentage of the bull regime that occurred in January, which is calculated as the ratio of the total number of Januaries classified in the bull regime to the total number of months classified in this regime. The numbers in the parenthesis are the total number of months classified in the bull regime.

*In drawing an inference on the unobserved state, we estimate the D2 and D3 portfolios with a five state Markov switch instead of 7 and 6, in part because it makes it easier to make comparisons with other portfolios.

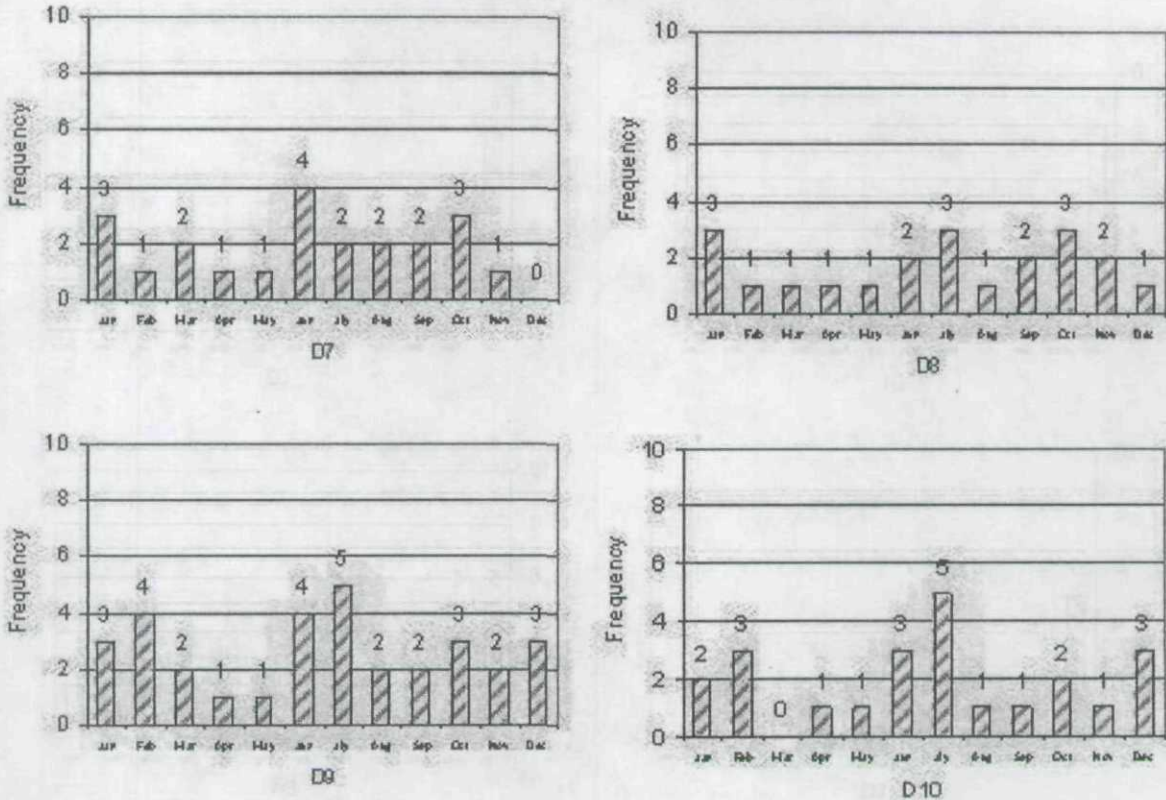
FIGURE 3
FREQUENCY OF THE BULL REGIME



The height of these bar graphs is the number of months assigned to the bull regime in each calendar month.

Figure 3 Contd.

FIGURE 3 CONTINUED
FREQUENCY OF THE BULL REGIME



Conclusions and Implications for Policy

In this paper, applying the Markov-switching model to the NYSE stock equally-weighted monthly returns, we find there are five regimes instead of two regimes as it has been documented in the traditional January effect literature. Through the inferential probabilities on these five regimes and the derived regime classification, we find no evidence of the January effect for the market as a whole. However, the January effect is found for low capitalization stock portfolios. Therefore, our more robust time series analysis research approach reinforces the existence of the January size effect for the small cap stocks.

We use a Markov-switching model to estimate the transition probabilities of stock returns in a regime shift model. The transition probabilities from our estimation indicate the chance to stay in the same normal regime next period is 99 per cent. This shows that the stock

market behavior is very stable in the normal regime. However, there are always random shocks that occur in our economy similar to the stock market crash in the other regimes. The transition probabilities for the other regimes do not show an instant return to the normal regime. Therefore, the cycles of bull and bear markets are usually observed in the real world.

From these results, two policy implications may be derived. If the transition probability reflects the outcome of the economic policies, this indicates that the hose policies may not be very effective in reducing the market cycles. The probability of staying in the same bear regime is still high. The second implication is about the January effect. When we analyze the details of the months assigned to the bull market, this paper shows that the January effect cannot be found for NYSE equally-weighted monthly market stock returns. Therefore, the investors will not experience high mean returns in January.

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