The Monthly Effect and the Day of the Week Effect in the American Stock Market

Bing Xiao[1]

[1] Management Science, Université d'Auvergne, CRCGM EA 38 49 Université d'Auvergne, Auvergne, France

Correspondence: Bing Xiao, PhD in Management Science, Université d'Auvergne, CRCGM EA 38 49 Université d'Auvergne, Auvergne, France.

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Abstract

This paper examine the recent evolution of seasonal anomalies in the American stock market. This study was based on daily data from the Russell 3000 index over the 2000-2015 period. We examine the recent evolution of the week effect and the monthly effect, and we investigate seasonal patterns in economically favourable times and unfavourable times. We use a UCM model and ARCH model. We find evidence for fixed seasonality with a positive and significant monthly effect. Our study confirms January and December effects to the values of the Russell 3000 index, but we don't find evidence of the day of the week effect.

Keywords: stock markets, seasonal anomalies, efficiency, economic cycles, monthly effect, day of week effect, ARCH

1. Introduction

In developed stock markets, anomalies are a well-documented stylized fact. One of the anomalies in the American stock markets is the seasonal effect. Seasonalities in stock returns are among the most robust findings. There are two sorts of seasonalities: high frequency seasonality: for example the day of the week effect and the turn of the month effect. And the low frequency seasonality: such as January or February effect. In this paper, we focused on the day of the week and the monthly regularities.

The seasonal effect generates a large amount of interest in academic circles. The major reason is theoretical: if it were possible to show that investment strategy based on seasonality is capable of systematically beating the market, the efficient market theory would be faulty. The seasonal effect also poses a problem with regards to the validity of the Capital Asset Pricing Model (CAPM), validity according to which the expected yield of securities depends on the systematic risk level (the Beta). According to behavioural finance researchers, seasonal anomaly is proof of the irrationality of individuals. On the other hand, researchers who support the concept of rationality suggest that seasonal effect can be attributed to risk factors other than the market.

Some anomalies seem to disappear after they are documented in the finance literature: Does their disappearance reflect sample selection bias, so that there was never an anomaly in the first place? Or does it reflect the actions of practitioners who learn about the anomaly and trade so that they make profitable transactions (Schwert 2003)? In this paper, we analyse the recent evolution of the seasonal anomalies in the American stock markets. Thus, our paper contributes to the existing finance literature by investigating the seasonal anomalies during the recent period. Our second contribution is to re-examine the weak form of the efficient markets hypothesis (EMH) using daily American stock market data.

The rest of the paper is organized as follows. Section II reviews the literature. Section III introduces Data and methodology. Our empirical findings are discussed in Section IV. Section V concludes the paper.

2. Literature Review

A considerable body of literature has been produced that documents seasonal patterns in stock returns. Empirical findings have established that mean stock returns vary over the days of the week A day of the week effect was detected in the U.S. market by Cross (1973), French (1980), Gibbons and Hess (1981), Rogalski (1984). These studies document a negative mean return for Monday and a positive mean return for Friday. Mookerjee and Yu (1999) found that the higher returns on a particular weekday are due to the higher risk assumed on that day: a higher standard deviation is associated with higher daily mean returns except Monday. French (1980) hypothesized that the standard deviation for Monday returns should be the highest because a greater number of shocks can manifest themselves over the weekend break. The model to estimate the day of the week effect given by Mookerjee and Yu (1999) is as follow:

$$R_t = a_0 + a_1 d_{1,t} + a_2 d_{2,t} + a_3 d_{3,t} + a_4 d_{4,t} + e_t \quad (1)$$

Where R_t is the return on day t and $d_{i,t}$ is a dummy variable that takes the value of one for a given day of the week and is zero otherwise.

The month-of-the-year effect was found by Roll (1983) and Ritter (1988). They found a positive January effect and a negative December effect. Keim (1983) and Reingnum (1983) showed that much of the abnormal return to small firms (measured relative to the CAPM) occurs during the first two weeks in January. Roll (1983) hypothesized that the investors might want to realize for income tax purposes before the end of the year, the selling pressure might reduce prices of small capitalization stocks in December, leading to a rebound in early January as investors repurchase these stocks to reestablish their investment position. Cooper et al. (2006) report US evidence that returns in January have predictive power for returns over the subsequent 11 months. Chen and Chien (2011) explained the January effect with the theoretical arguments drawn from behavioral finance, they documented that there will be a January effect when the whole market had positive performance growth in the preceding year.

To test the difference between the monthly effect, Mookerjee and Yu (1999) give the following regression:

$$R_t = a_0 + a_1 D_{me} + e_t \quad (2)$$

Where R_t is the holding period return for day t and D_{me} is a dummy variable that takes the value one for the first and last days of the month and takes the value of zero otherwise.

The seasonal effect is one of the anomalies of the financial market. For example, if there is a negative day-of-the-week effect, the rational arbitrageurs could sell stocks short in the morning of that day and buy them back the next day. Such trading activity would eventually result in the disappearance of the effect. Fama and French (1989) find that expected returns contain risk premiums that move inversely with business condition. Kim and Burnie (2002) advanced the hypothesis according to which size effect might be driven by the economic cycle. L'Her, Masmoudi and Suret (2002) also pointed out that risk premiums vary according to economic conditions. DeStefano (2004) find that stock returns decrease throughout economic expansions and become negative during the first half of recession.

The evidence regarding seasonal effects is rather mixed as conclusions from various studies seem to depend heavily on the particular choice of sample period. For this reason, we associated the seasonal anomalies with the economic cycles to research a new explanation to this issue. In this paper, we focus exclusively on the day of the week effect and the monthly effect.

3. Data and Methodology

3.1 Data and Cycles

The Russell 3000 Index measures the performance of the largest 3,000 U.S. companies representing approximately 98% of the investable U.S. equity market. Our sample contains 3904 daily observations from the Russell 3000 (February 2000 to September 2015) taken from Factset. Factset is a financial database and designates a software editor. The company provides financial information and analytical software for investment professionals. Factset also offers access to data for analysts, portfolio managers and investment banks.

The objective of this paper is to study the recent evolution of seasonal anomalies in the American stock market. To this end, we will define the economic cycles between 2000 and 2015 in the U.S. The OECD system of Composite Leading Indicators (CLIs) is designed to provide early signals of turning points in business cycles – fluctuation of the economic activity around its long term potential level. This approach, focusing on turning points (peaks and troughs), results in CLIs that provide qualitative rather than quantitative information on short-term economic movements. The phases and patterns in CLIs are likely to be followed by the business cycle, with the turning points of the CLI consistently preceding 6 – 9 months of those of the business cycle.

Our study covers the period from 2000 to 2015. To be able to highlight the relationship between the seasonal effects and the economic cycle, we have to give an objective description of the economic environment. We chose to break down the economic cycle into two distinct phases: one phase that is favourable to companies and one that is unfavourable. The problem that arises is to precisely determine the start and end date of each of these phases.

In order to limit economic cycles, we have chosen to distinguish two states of the economic cycle – expansion and recession – thus giving a macroeconomic approach to the cycle. The OCDE composite leading indicator was conceived to indicate turning points in the economy. Figure 1 plots the evolution of the index Russell 3000 from 2000 to 2015. We use the algorithm of Bry and Boschan (1971) (VBA programming) for the datation of the cycles, this allows us to highlight three identified "peak to peak" cycles during the period from February 2000 to September 2015: February 2000 – January 2003; January 2003 – July 2007, July 2007 – March 2009 and March 2009 – September 2015.

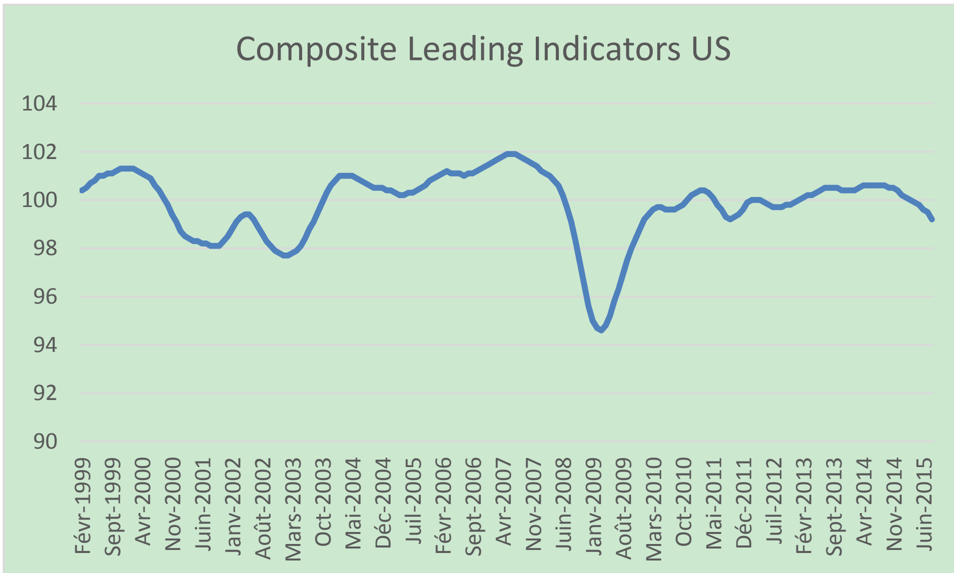

Figure 1. Composite leading indicators US 2000 to 2015

3.2 Econometric Models

3.2.1 Unobserved Components Model

We approach our series of Russell 3000 by using an unobserved components time series model (UCM) (see Harvey 1989 and Girardin and Liu 2005). The model allows us to decompose the index I_t between three components given by:

$$I_t = \mu_t + \gamma_t + \varphi_t + \varepsilon_t \qquad \varepsilon_t \sim NID(0, \sigma^2_{\varepsilon}), \tag{3}$$

Where μ_t, γ_t and ε_t represent trend, seasonal and irregular components respectively. The trend and seasonal components are modeled by linear dynamic stochastic processes which depend on disturbances. They are formulated in a flexible way and can change over time rather than being deterministic. φ_t corresponds to a set of explanatory and dummy variables.

The trend component is simply modeled as a random walk process according to the structure of our data:

$$\mu_{t+1} = \mu_t + \eta_t, \qquad \eta_t \sim NID(0, \sigma^2_{\eta}), \tag{4}$$

Where NID $(0,\sigma^2)$ refers to a normally independently distributed series with mean zero and variance σ^2.

For the seasonal component, we want to study if for a given month, deviations from trend tend to be of the same sign from one year to the next. Let there be s seasons during the year, in our case s =12. We use a stochastic dummy variable seasonal model for the effect γ_t at time t:

$$\sum_{i=0}^{s-1} \gamma_{t-i} = \omega_t, \qquad \omega_t \sim NID(0, \sigma^2_{\omega}) \tag{5}$$

In this model, the sum of the seasonal effect has a zero mean although their stochastic nature allows them to evolve either slowly over time (when σ^2_{ω} is small) or quickly over time (when σ^2_{ω} is large). All disturbances are supposed to be mutually uncorrelated. If the variance is equal to zero, the seasonal effects are fixed and do not vary over time in contrast to the precedent specification (3). All models are estimated using maximum likelihood.

3.2.2 ARCH Model

It is a non-linear model which does not assume that the variance is constant, and it describes how the variance of the errors evolves ε_t. Many series of financial asset returns that provide a motivation for the ARCH class of models, is known as 'volatility clustering'. Volatility clustering describes the tendency of large changes in asset prices (of either sign) to follow large changes and small changes (of either sign).

Under the ARCH model, the "autocorrelation in volatility" is modeled by the conditional variance of the error term σ_t^2, to depend on the immediately previous value of the squared error, and ARCH(1) model takes the following form (See Angle 1982):

$$\varepsilon_t = Z_t \sigma_t \tag{6}$$

$$Z_t\ i.i.d., E(Z_t) = 0, var(Z_t) = 1$$

The form of ARCH (q) model is as follows where error variance depends on q lags of squared errors:

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} a_i \varepsilon_{t-i}^2 \tag{7}$$

4. Empirical Results

4.1 The Day of the Week Effect

Table 1 reports the mean and standard deviation of daily stock returns for the Russell 3000. For the whole period, returns have been negative. The lowest daily returns were found on Monday. Returns gradually build up to a peak on Thursday and then dip slightly on Friday. Table 2 reports the mean return by day of week during the expansion period and the recession period. The overall pattern is similar to that observed for the whole period; the Monday returns have been negative in the recession period. However, we don't find a Friday effect. Overall, the results are consistent with findings for other markets, except for the Friday effect. Table 1 and table 2 also report the standard deviation in daily returns, because it would be a source of insight into whether higher returns on a particular weekday are due to the higher risk assumed by an investor on that day. But we don't find that a higher standard deviation is associated with higher daily returns in our patterns.

Table 1. Mean and standard deviation (S.D.) of daily percentage return: day of the week during the whole period

Whole period (Feb 2000 – Sep 2015)	Observations	Mean	S.D.
Monday	780	-0.02779	0.0135
Tuesday	781	0.06029	0.0131
Wednesday	781	0.01801	0.0126
Thursday	780	0.04225	0.0129
Friday	780	-0.00115	0.0182

Table 2. Mean and standard deviation (S.D.) of daily percentage return: day of the week during the expansion and the recession period

	Recession Feb 00 – Jan 03	Expansion Jan 03 – Jul 07	Recession Jul 07 – Mar 09	Expansion Mar 09 – Sep 15
Monday	-0.08873	0.05246	-0.3824	0.02826
	(120) [0.0145]	(233) [0.00805]	(86) [0.02522]	(341) [0.0119]
Tuesday	-0.1692	0.06642	0.19396	0.10381
	(121) [0.01526]	(233) [0.00789]	(86) [0.02437]	(341) [0.01098]
Wednesday	-0,01335	0.08995	-0.29324	0.05994
	(120) [0.0159632]	(232) [0.0076]	(86) [0.02215]	(341) [0.01057]
Thursday	-0,04557	0.032	-0.301	0.13594
	(120) [0.01433]	(233) [0.0076]	(87) [0.02194]	(340) [0.01191]
Friday	-0.1165	0.0258	-0.02751	0.02737
	(120) [0.01407]	(233) [0.00712]	(86) [0.0174428]	(340) [0.0093]

In each case, the first row is the mean, in parenthesis is the number of observations and in brackets is the standard deviation.

In Table 3 below, we report results of the estimated variances of the different components of our unobserved components model. Column "Stochastic Trend" presents estimations for the basic stochastic component model. In column "Determinist", we introduce the determinist component. We don't find the day of the week effect by using the UCM model and the ARCH model. The coefficients are not significant and we don't observe the influence of economic condition in the day of week effect.

Table 3. Estimated variances for the unobserved components model

	Stochastic Trend			Determinist Trend		
	Coef.	**Std. Err.**	**Prob.**	**Coef.**	**Std. Err.**	**Prob.**
Determinist Trend				0.000131	0.000	0.045**
Stochastic Trend	0.0006139	0.000	0.000***			
C	6.027	0.0177	0.000***	7.0096	0.11378	0.708
Ar(1)	0.9540	0.0038	0.000***	0.99779	0.00087	0.000***
Monday	-0.00061	0.0005	0.224	-0.00047	0.000388	0.222
Thursday	-0.00021	0.0005	0.669	-0.00006	0.00049	0.904
Wednesday	-0.00022	0.0004	0.579	-0.00006	0.00051	0.93
Thursday				0.00017	0.00046	0.708
Friday	-0.00016	0.0004	0.720			
Log likelihood	11623.083			11518.13		
Iterations	11			13		

*, **, and *** indicate statistical significance at the 10, 5 and 1 percent levels, respectively.

4.2 The Monthly Effect

Table 4 reports the mean daily return by month during the expansion period and the recession period. For the whole period, we find the inversion of the December and January effect. In fact, there is a negative January effect and a positive December effect. The results obtained by analyzing the economic cycles confirm our findings, the December returns do better than the January returns. We find positive mean returns for March, April and May. Girardin and Liu (2005) explain that the speculators accumulate their holdings of stocks in the first 2 months of the year, during March and April, speculators would try to corner the market and bid up the price. From the end of April, speculators would try to reduce their holdings when the price is still high. After the middle of June, they would get money back from the sale of their stocks plus speculative profit, in order to pay back what they borrowed, over a half-year period, at the beginning of the year. This practice may also explain the bad performance in June returns.

Table 4. Daily percentage average return of monthly effect

	Whole period	Recession Feb 00 – Jan 03	Expansion Jan 03 – Jul 07	Recession Jul 07 – Mar 09	Expansion Mar 09 – Sep 15
January	-0.02268	0.05361	0.02068	-0.31965	0.01922
February	-0.01428	-0.29148	-0.00271	-0.3442	0.17958
March	0.06005	-0.05066	0.00687	-0.31568	0.19454
April	0.10104	0.06168	0.07888	0.22367	0.10988
May	0.0215	-0.0001	0.09706	0.08661	-0.03405
June	-0.06303	-0.22638	0.01823	-0.41037	-0.02827
July	0.01963	-0.20661	0.02921	-0.14317	0.11321

August	0.02612	-0.11951	0.03967	0.06785	-0.06394
September	-0.03766	-0.48507	0.03681	-0.12721	0.07316
October	0.06357	0.14514	0.10286	-0.32679	0.13179
November	0.04675	0.05735	0.13085	-0.26664	0.08769
December	0.06559	-0.04057	0.09873	0.04729	0.1003

In Table 5 on the following page, we report results of the estimated variances of the different components of our unobserved components model. Column “month” presents estimations for the seasonality in the recession cycle. In column “month*dummy”, we introduce the effect of expansion. We find a significant and positive May effect and December effect while the impact for January is not significant.

Table 5. Estimated variances for the unobserved components and ARCH (1) model

	Month			Month*Dummy		
	Coef.	Std. Err.	Prob.	Coef.	Std. Err.	Prob.
C	0.00324	0.001207	0.007			
January	0.000681	0.0008473	0.422	0.0008296	0.0015308	0.588
February				0.0021522	0.0015961	0.178
March	0.003723	0.0010347	0.000***	-0.0013995	0.0015577	0.369
April	0.005841	0.0011044	0.000***	-0.0041574	0.0015889	0.009
May	0.004447	0.0011509	0.000***	-0.0025409	0.0016446	0.122
June	0.000673	0.0012742	0.597			
July	0.001310	0.0010831	0.226	0.0002728	0.0016043	0.865
August	0.003309	0.001107	0.003***	-0.0014146	0.0016191	0.382
September	-0.003134	0.0007942	0.000***	0.0053807	0.0014353	0.000***
October	0.004207	0.0007596	0.000***	-0.0019903	0.0014168	0.160
November	-0.00001	0.0007852	0.903	0.00224478	0.0014312	0.116
December	0.003425	0.0008798	0.000***	-0.0015925	0.0015643	0.309
AR(1)	-0.23285	0.0074205	0.000***			
C	0.000094	2.15 e-06	0.000***			
ARCH (1)	0.4942827	0.026	0.000***			

*, **, and *** indicate statistical significance at the 10, 5 and 1 percent levels, respectively.

5. Conclusions and Discussions

We have used UCM and ARCH model to detect the presence of seasonality over the 2000 to 2015 period for the American stock market. It would seem that the monthly effect persists. Our results point to the fact that the economic cycles do not have an effect on the observed pattern in daily stock returns. However, it is acknowledged in existing literature that, on a general level, seasonality is often very sensitive to the presence of outliers. And the inversion of the day of the week effect and the monthly effect is highly dependent on the estimation method and sample period in particular. Such an anomaly vanishes after correcting for non-normality (Girardin and Liu 2005). This being said, a reversed monthly effect during certain periods does not necessarily imply a disappearance of the seasonality. For further analysis of seasonality in the American stock market, we think we have to analyse if investment strategy based on seasonality is capable of systematically beating the market.

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