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Overreaction of US stock markets to interest rate news

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Abstract

The purpose of this paper is to measure overreaction to interest rate news for three US stock market indices. This is a different kind of overreaction than the one studied in previous literature. It relies on observations from the field of psychology that some individuals suffer from winter depression. Those individuals may even affect trading in financial markets, or at least introduce significant noise trading. The paper provides empirical evidence that there indeed exists overreaction to interest rate changes during January and during the northern winter (December, January, and February). There is weak evidence that overreaction typically occurs in January rather than in winter, because significance levels are lower for January effects.

Introduction

There are at least four theoretical channels of transmission from interest rates to stock markets. Two of them rely on inflation effects. The first of these two is based on the CAPM model, whereby the following relation holds:

$$E(k_j) = rf + \beta_j (E(km) - rf) \tag{1}$$

In equation (1) k_j is the return on security or portfolio j, rf is the risk-free rate of return, km is the return on the average stock, or on a stock market index, β_j is the systematic risk of security or portfolio j, and $E(.)$ is the current expectation operator. Finance theory predicts that an increase in inflation will shift the CAPM line upward parallel-wise, leaving the slope constant, i.e. leaving $(E(km) - rf)$ constant (Brigham and Houston, 2007, p. 276). This means that both km and rf increase by the increase in inflation. Therefore, a higher inflation rate leads to both a higher stock index return and a higher interest rate, resulting in a positive relation between the stock market and interest rates.

The second channel of transmission relies on the concept of hedging: stock markets should hedge against inflation. Here again a rise in inflation leads to a higher stock index return in order to compensate the investor for the loss in purchasing power.

The above two channels of transmission assume a constant *ex ante* real interest rate $E(r)$, so that changes in inflation lead automatically to changes in nominal interest rates. If the nominal interest rate is i and if the forecast inflation rate is $E(\pi)$ then the following holds:

$$(1+i) = (1+E(r))(1+E(\pi)) \Rightarrow i \approx E(r) + E(\pi) \tag{2}$$

Equation (2) shows that, if the *ex ante* real rate $E(r)$ is constant, then the nominal interest rate changes in proportion to changes in expected inflation and, hence, nominal interest rates predict expected inflation. Thus the difference between actual inflation π and the nominal interest rate i would measure unanticipated inflation.

The third channel of transmission works through changes in the Present Value (PV) of future corporate earnings. A higher interest rate is passed on as a higher discount rate and this affects the PV of cash flows negatively. If one assumes a perpetual cash flow stream Y, then the PV of this perpetuity at the market rate k is equal to:

$$PV = \frac{Y}{k} \tag{3}$$

Equation (3) shows clearly the negative relation between interest rates and the PV of cash flows. In turn, lower discounted cash flows affect negatively the value of the firm.

The relation between interest rates and stock markets is expected to be negative, contrary to the above two channels of transmission. A related effect is that higher interest rates occur in tandem with more variability of interest rates, with the latter increasing uncertainty in the economy and reducing expected cash flows.

The last channel of transmission is through the Gordon (1962) dividend model and the concept of duration. The Gordon model can be summarized as follows:

$$P_0 = \frac{D_1}{k - g} \tag{4}$$

Equation (4) assumes a constant growth in dividends g, and relates the next-period dividend D_1 to today's price of the equity P_0. Taking the derivative of P_0 with respect to k, the cost of equity, one obtains:

$$\frac{d(P_0)}{d(k)} = -\frac{D_1}{(k-g)^2} \tag{5}$$

Dividing equation (5) by P_0 and rearranging, one gets (Baz and Chacko, 2004):

$$\frac{d(P_0)}{P_0} = -\frac{D_1}{(k-g)^2}\frac{(k-g)}{D_1}d(k) = -\frac{1}{(k-g)}d(k) \tag{6}$$

In equation (6) the duration of the stock is equal to $1/(k-g)$. This equation shows plainly that changes in interest rates have a negative impact on stock returns, with the proportionality factor being equal to the stock (Macaulay) duration.

To summarize, the above theoretical approaches do not provide a definite conclusion as to on the relation between interest rates and the stock market. Two theories predict a positive relation, while the other two theories predict a negative relation. In addition, it is not clear whether interest rates should be taken in their levels or in their first-differences, as in equation (6). The issues ought to be resolved empirically. Fama and Schwert (1977) is the classic paper on the subject. Their results have been replicated by later research (Campbell, 1987; Ferson, 1989; and Shanken, 1990). The unanimous conclusion from this research is that nominal interest rates and inflation are negatively correlated with the stock market. Unfortunately this research models the relation in terms of the level of the interest rate: a higher level of the interest rate (or a higher inflation rate) is associated with low stock returns. The problem with such a working assumption is that, while stock returns are stationary in distribution, interest rates behave as if they follow a non-stationary statistical process, i.e. a random walk. Therefore this initial research has been statistically misspecified. Azar (2002) has argued against such a misspecification, naming it a *model anomaly*. Azar (2007) has estimated empirically equation (6), and has found supportive evidence for this transmission channel. Léon (2008) has also found a negative relation between *changes* in interest rates - which he calls volatility of interest rates - and stock returns for the Korean market. Unfortunately he acknowledges that the likelihood ratio test which he conducted failed to reject the null hypothesis of no effect of changes in interest rates on stock returns.

This paper is organized as follows. The second section describes the empirical hypotheses of this paper which are based on the assumption of a cognitive bias. The following section presents the empirical results. Section IV discusses the implications of the analysis. The last section has some concluding comments.

Data & Theory

If interest rates follow a random walk, or technically a unit root process, then *changes* in interest rates are unpredictable given the current information set. Therefore changes in interest rates are news. It is the purpose of this paper to evaluate the effect of this news component on three stock index returns: those of the S&P 500, the DJIA, and the NASDAQ. The returns are calculated as the first-differences of the logs.

The data is taken from the web site of EconStats and the US Federal Reserve Board. The S&P 500 data is the monthly close from 1945:1 to 2008:5, although the data is presently available only starting from 1950:1 instead of from 1945:1. The DJIA data is the monthly close from 1945:1 to 2008:5. Finally the NASDAQ data is the monthly close from 1972:2 to 2008:5. The interest rate is the monthly 3-month T-Bill rate.

The analysis intends not only to estimate the impact of changes in interest rates on stock index returns, but also to test a specific cognitive bias from psychology, psychiatry, and behavioral finance.[1] This bias has not received the attention that it deserves in the literature. And, to the knowledge of the author, this paper is the first to test for such a bias in finance. The cognitive bias that is the object of this paper is what is known as Seasonal Affective Disorder, or SAD (Lurie *et al*., 2006), or it is sometimes referred to as 'winter depression' (see for a recent application to Sweden: Rastad *et al*., 2005). It is considered to be a major depression and is listed in the 1994 version of *The Diagnostic and Statistical Manual of Mental Disorders* (DSM-IV). It is hypothesized that because of this depression some stock market traders, or at least some individual noise traders, overreact to interest rate news in the winter. SAD is more frequent with the educated and the younger population (Rastad *et al.*, 2005), and such characteristics apply to market traders. The paper tests a winter overreaction effect and a January overreaction effect. The results produce marginally more support for a January effect than for a winter effect. In any case there is general support for overreaction, maybe because of the existence of this cognitive bias.

Overreaction has been studied within a different context (De Bondt and Thaler, 1985, 1987): prior loser stocks perform well later, and prior winner stocks perform badly later. More modern evidence on this kind of overreaction for the UK market is found in Dissanaike (1998). Recently however, Ajayi *et al.* (2006) reject the overreaction hypothesis in favor of the 'uncertain information hypothesis,' whereby traders place a discount on stock prices because of the uncertainty inherent in news events. Unfortunately this literature on overreaction does not tackle the particular cognitive bias that is tested in this paper.

The statistical procedure is to form a dummy variable for the winter season (December, January, and February), or just for January, and to enter this dummy as an interactive variable with the change in interest rates. The hypothesis is that in the winter, or at least in January, the effect of interest rate news is more pronounced, meaning that interest rate changes produce a larger impact in absolute value on stock index returns. Mathematically the model is as follows:

$$\Delta[Log(Y_t)] = \alpha_0 + \alpha_1 X_t [\Delta(i_t)] + \alpha_2 (1 - X_t)[\Delta(i_t)] + \varepsilon_t$$
$$\varepsilon_t \text{ is i.i.d. } \left(0, \sigma_t^2\right) \text{ and } \quad \sigma_t^2 = \beta_0 + \beta_1 \sigma_{t-1}^2 + \beta_2 \varepsilon_{t-1}^2 \qquad (7)$$

Equations (7) incorporate two sub-equations, one for the conditional mean, and one for the conditional variance. In the conditional mean equation stock index returns $\Delta[Log(Y_t)]$ are related to two interactive variables: the impact of interest rate changes in the winter (or in January), and the impact of interest rate changes in the other months. The variable X_t represents the two dummy variables in the two specifications of the model. X_t is either $D1_t$, which is 1 for January and 0 otherwise, or $D2_t$, which is 1 in the winter (i.e. in December, January, and February), and 0 otherwise. If the impact during the winter (or in January) α_1, is higher in absolute value than the impact during the other months (α_2), then the hypothesis of overreaction is supported. The conditional variance equation is assumed to follow a GARCH(1,1) process (Engle, 1982, 1983; Bollerslev, 1986), and is included in the regressions of all three stock market indices: the S&P 500, the DJIA, and the NASDAQ series.

There is evidence that the S&P 500 has a break above the level of 1000 (Azar, 2008). This evidence shows that the S&P 500 follows a given statistical process if its level is above 1000, and a different statistical process if its level is below 1000, making the level of 1000 a psychological barrier. More specifically the statistical process is non-stationary below the level of 1000, necessitating first-differencing, as in equations (7), while it is stationary and mean-reverting to a value of 1342.87 above the level of 1000. This evidence prompts me to test whether this barrier is also effective in what regards the impact of interest rate changes.

For this purpose another interactive dummy variable with the change in interest rates is defined. It takes a value 1 if the S&P 500 is above 1000 and 0 otherwise. Hypothesis testing shows that interest rate changes have a statistically insignificant impact when the S&P 500 is above 1000 and a statistically significant impact when the S&P 500 is below 1000. This also applies to winter and January reactions. These reactions have also statistically insignificant impacts when the S&P 500 is above 1000. Nonetheless the impact on stock returns when the S&P 500 is below 1000 is significant statistically in the winter, in January, and in the other months. Moreover hypothesis testing shows that the impacts in the winter and in January are much larger in absolute value than the impact in the other months: the cognitive bias hypothesis of a winter depression receives the needed support.

[1] Surveys of behavioral economics and finance are plentiful: Thaler (1999), Kahneman and Tversky (2000), Shleifer (2000), Barberis and Thaler (2003), Camerer *et al.* (2004), and Baker *et al.* (2007).

Empirical Results

First, and in order to ascertain the random walk behavior of interest rates, Phillips and Perron unit root tests with a constant and a trend are carried out on the T-Bill rate for the two sample sizes defined previously for the three stock market indices (Table 1). The results show clearly that the level of the T-Bill rate is non-stationary, i.e. it follows a process integrated of order 1. The unit root processes are not rejected at conventional confidence levels. However the unit root null hypothesis is rejected for the first-difference of the T-Bill rate with actual probability levels much less than 0.01. This is evidence that changes in the T-Bill rate are unpredictable with the current information set. Following the new classical literature on rational expectations only unexpected changes are modeled to have an effect on stock markets. Expected changes are assumed to get incorporated into prices rather quickly.

Table 1. Probabilities of the Phillips and Perron unit root tests with a constant and a trend.

Sample	i_t	$\Delta(i_t)$
1945:1 2008:5	0.3664	0.0000
1971:2 2008:5	0.1929	0.0000

Notes: i_t is the monthly 3-month T-Bill rate. The symbol Δ is for the first-difference operator. A probability that is lower than the Type I error of 0.05 is evidence of the rejection of the null hypothesis of non-stationarity.

Table 2 provides the results of estimating the first model, i.e. equations (7). The presence of conditional heteroscedasticity necessitated the estimation of a GARCH(1,1) model for the conditional variance of the three stock market indices: the S&P 500, the DJIA, and the NASDAQ. The results in Table 2 show that the ultimate residuals suffer neither from serial correlation nor from further conditional heteroscedasticity. These ultimate residuals in Table 2 are the standardized residuals from the multiple regressions of the stock returns, estimated with a GARCH(1,1) model for the conditional variance. These standardized residuals are calculated by dividing the regression residuals by the conditional standard deviations. The Ljung-Box Q-statistic is applied to both the standardized residuals and their squares. In Table 2 all reported probabilities for the Q-statistics are higher than the 5% Type I error. Moreover, one can invoke the Central Limit Theorem for asymptotic normality of the residuals since the sample sizes are large.

Table 2. Estimation of the following model:

$$\Delta[Log(Y_t)] = \alpha_0 + \alpha_1 X_t[\Delta(i_t)] + \alpha_2(1 - X_t)[\Delta(i_t)] + \varepsilon_t$$

$$\varepsilon_t \text{ is i.i.d. } \left(0, \sigma_t^2\right) \text{ and } \sigma_t^2 = \beta_0 + \beta_1\sigma_{t-1}^2 + \beta_2\varepsilon_{t-1}^2$$

Y_t	S&P 500	S&P 500	DJIA	DJIA	NASDAQ	NASDAQ
X_t	$D1_t$	$D2_t$	$D1_t$	$D2_t$	$D1_t$	$D2_t$
Sample	1945:1 2008:5	1945:1 2008:5	1945:1 2008:5	1945:1 2008:5	1971:2 2008:5	1971:2 2008:5
Sample size	760	760	760	760	447	447
α_0	0.006173 (4.250)	0.006205 (4.251)	0.005537 (3.892)	0.005601 (3.918)	0.007398 (2.538)	0.007371 (2.539)
α_1	-0.04297 (-2.577)	-0.03016 (-2.739)	-0.04335 (-3.232)	-0.03069 (-3.099)	-0.06907 (-2.594)	-0.04945 (-2.510)
α_2	-0.01193 (-3.847)	-0.01020 (-3.327)	-0.01230 (-4.044)	-0.01061 (-3.495)	-0.01383 (-2.571)	-0.01109 (-1.997)
β_0	0.000090 (2.762)	0.000091 (2.737)	0.000080 (2.142)	0.000085 (2.185)	0.000248 (2.103)	0.000249 (2.134)
β_1	0.85715 (25.328)	0.85512 (24.804)	0.88753 (22.496)	0.88346 (22.175)	0.83457 (15.560)	0.82600 (15.274)
β_2	0.09120 (3.370)	0.09311 (3.368)	0.06428 (2.634)	0.06593 (2.693)	0.10196 (2.965)	0.11157 (3.041)
$\alpha_1 - \alpha_2$	-0.03105 (-1.825)	-0.01995 (-1.741)	-0.03106 (-2.247)	-0.02009 (-1.927)	-0.05525 (-2.027)	-0.03836 (-1.831)
Probabilities of	On $[\varepsilon_t / \sigma_t]$	On $[\varepsilon_t / \sigma_t]$	On $[\varepsilon_t / \sigma_t]$	On $[\varepsilon_t / \sigma_t]$	On $[\varepsilon_t / \sigma_t]$	On $[\varepsilon_t / \sigma_t]$
Q(12)	0.734	0.661	0.863	0.823	0.362	0.362
Q(24)	0.757	0.730	0.813	0.788	0.719	0.685
Q(36)	0.969	0.959	0.925	0.911	0.816	0.782

Probabilities of	On $[\varepsilon_t / \sigma_t]^2$	On $[\varepsilon_t / \sigma_t]^2$	On $[\varepsilon_t / \sigma_t]^2$	On $[\varepsilon_t / \sigma_t]^2$	On $[\varepsilon_t / \sigma_t]^2$	On $[\varepsilon_t / \sigma_t]^2$
Q(12)	0.918	0.899	0.564	0.495	0.999	0.999
Q(24)	0.981	0.969	0.947	0.902	0.999	0.999
Q(36)	0.971	0.964	0.901	0.873	0.999	0.999

Notes: i_t is the monthly 3-month T-Bill rate. The T-Bill rate is in percent per annum. $D1_t$ is a dummy variable that takes the value 1 in January and 0 otherwise. $D2_t$ is a dummy variable that takes the value 1 in December, January, and February, and 0 otherwise. Q(k) is the Ljung-Box Q-statistic for lag k. Only probabilities of the Q-statistics are reported. A probability that is higher than the Type I error of 0.05 is evidence of no serial correlation. T-statistics are in parenthesis. The symbol Δ is for the first-difference operator. Log is the natural logarithm.

Table 2 reports the estimation of equations (7) for the three stock market indices: the S&P 500, the DJIA, and the NASDAQ. The coefficients α_1 and α_2 are all statistically significant at the 5% two-tailed test, and have the expected negative sign. The difference between α_1 and α_2 is statistically significant for all four regressions at a confidence level below 10% with a two-tailed test, the lowest t-statistic in absolute value being 1.741, and the highest being 2.247. The estimates of this difference show that $|\alpha_1| > |\alpha_2|$ with $|\alpha_1 - \alpha_2|$ having almost twice the impact of $|\alpha_2|$. This difference measures the extent of overreaction. This is evidence for a winter and a January overreaction. The t-statistics of the overreaction are consistently higher for the January dummy than for the winter dummy. Hence there is weak evidence that the overreaction is a January phenomenon, and not a winter one.

Table 2 also reports the estimation of the conditional variances in equations (7). The sum $\beta_1 + \beta_2$ is less than 1 for all six regressions. This means that the conditional variances are mean-reverting, although there is a high persistence in their behavior: mean reversion is slow and the half lives are between 10.57 and 14.04 months.

Table 3 reports the results of testing the joint hypothesis that $\alpha_1 = 0$ and $\alpha_3 = 0$ in the following model:

$$\Delta[Log(Y_t)] = \alpha_0 + \alpha_1 X_t [\Delta(i_t)] D3_t + \alpha_2 X_t [\Delta(i_t)](1 - D3_t) +$$

$$\alpha_3 (1 - X_t)[\Delta(i_t)] D3_t + \alpha_4 (1 - X_t)[\Delta(i_t)](1 - D3_t) + \varepsilon_t$$

$$\varepsilon_t \text{ is i.i.d. } (0, \sigma_t^2) \text{ with } \sigma_t^2 = \beta_0 + \beta_1 \sigma_{t-1}^2 + \beta_2 \varepsilon_{t-1}^2 \qquad (8)$$

In equations (8) a new interactive dummy variable $D3_t$ is introduced to equations (7). This dummy takes the value 1 if the S&P 500 is greater than 1000 and 0 otherwise. In other terms the variable $(1 - D3_t)$ takes the value 1 if the S&P 500 is below 1000, and zero otherwise. The joint test ($\alpha_1 = 0$ and $\alpha_3 = 0$) purports to show whether the behavior of the stock indices varies across the psychological barrier of 1000 of the S&P 500. The result of the hypothesis test is that the joint null hypothesis of $\alpha_1 = 0$ and $\alpha_3 = 0$ fails to be rejected for all six regressions, with the lowest probability level being 0.262 (see Table 3). Hence there is a different data generation process when the S&P 500 is above 1000.

Table 3. Testing the joint hypothesis:

$\alpha_1 = 0$ and $\alpha_3 = 0$ in the model:

$$\Delta[Log(Y_t)] = \alpha_0 + \alpha_1 X_t [\Delta(i_t)] D3_t + \alpha_2 X_t [\Delta(i_t)](1 - D3_t) +$$

$$\alpha_3 (1 - X_t)[\Delta(i_t)] D3_t + \alpha_4 (1 - X_t)[\Delta(i_t)](1 - D3_t) + \varepsilon_t$$

$$\varepsilon_t \text{ is i.i.d. } \left(0, \sigma_t^2\right) \text{ with } \sigma_t^2 = \beta_0 + \beta_1 \sigma_{t-1}^2 + \beta_2 \varepsilon_{t-1}^2$$

Y_t	S&P 500	S&P 500	DJIA	DJIA	NASDAQ	NASDAQ
X_t	$D1_t$	$D2_t$	$D1_t$	$D2_t$	$D1_t$	$D2_t$
Sample	1945:1 2008:5	1945:1 2008:5	1945:1 2008:5	1945:1 2008:5	1971:2 2008:5	1971:2 2008:5
Sample size	760	760	760	760	447	447
Probability of the actual χ^2 on the joint null: $\alpha_1 = 0$ $\alpha_3 = 0$	0.4327	0.3113	0.7199	0.7196	0.2785	0.2616

Notes: i_t is the monthly 3-month T-Bill rate. $D3_t$ is a dummy variable that takes the value 1 if the S&P 500 > 1000, and 0 otherwise. $D1_t$ is a dummy variable that takes the value 1 in January and 0 otherwise. $D2_t$ is a dummy variable that takes the value 1 in December, January, and February, and 0 otherwise. A probability of the actual χ^2 higher than the Type I error of 0.05 is evidence of the failure to reject the null hypothesis. The symbol Δ is for the first-difference operator. Log is the natural logarithm.

In the following regressions the constraint that $\alpha_1 = 0$ and $\alpha_3 = 0$ in equations (8) is imposed in the analysis and the new model is:

$$\Delta[Log(Y_t)] = \alpha_0 + \alpha_1 X_t [\Delta(i_t)](1 - D3_t) + \alpha_2 (1 - X_t)[\Delta(i_t)](1 - D3_t) + \varepsilon_t$$

$$\varepsilon_t \text{ is i.i.d. } \left(0, \sigma_t^2\right) \text{ and } \sigma_t^2 = \beta_0 + \beta_1 \sigma_{t-1}^2 + \beta_2 \varepsilon_{t-1}^2 \quad (9)$$

Table 4 reports the results of estimating equations (9), which are applied to the three stock market indices: S&P 500, the DJIA, and the NASDAQ. The coefficients α_1 and α_2 are all statistically significant and have the expected negative sign. The highest t-statistic in absolute value is 4.330, and the lowest is 2.164. The difference α_1 - α_2, which measures the extent of overreaction, is negative and is statistically significant for all six regressions. The highest t-statistic in absolute value is 2.778 and the lowest is 2.104. Moreover, the difference α_1 - α_2 is almost twice the value of α_2. Therefore, overreaction is indeed a feature of the data. The cognitive bias that I have hypothesized does find support for three different stock market indices. The results tend to favor a January effect over or a winter effect, as the t-statistics for the January overreaction are higher than those for the winter. The findings are especially interesting because the S&P 500 and the DJIA are large-cap indices, whereas the NASDAQ is a small-cap index. Therefore the results are not driven by a January or turn-of-the-year positive excess return, which is mostly apparent with small-cap stocks (Schwert, 2003).

Table 4. Estimation of the following model:

$$\Delta[Log(Y_t)] = \alpha_0 + \alpha_1 X_t [\Delta(i_t)](1 - D3_t) + \alpha_2 (1 - X_t)[\Delta(i_t)](1 - D3_t) + \varepsilon_t$$

$$\varepsilon_t \text{ is i.i.d. } \left(0, \sigma_t^2\right) \text{ and } \sigma_t^2 = \beta_0 + \beta_1 \sigma_{t-1}^2 + \beta_2 \varepsilon_{t-1}^2$$

Y_t	S&P 500	S&P 500	DJIA	DJIA	NASDAQ	NASDAQ
X_t	$D1_t$	$D2_t$	$D1_t$	$D2_t$	$D1_t$	$D2_t$
Sample	1945:1 2008:5	1945:1 2008:5	1945:1 2008:5	1945:1 2008:5	1971:2 2008:5	1971:2 2008:5
Sample size	760	760	760	760	447	447
α_0	0.006048 (4.212)	0.006072 (4.196)	0.005468 (3.881)	0.005544 (3.908)	0.007172 (2.492)	0.007102 (2.477)
α_1	-0.05186 (-3.158)	-0.03721 (-3.165)	-0.05030 (-3.932)	-0.03560 (-3.498)	-0.08237 (-3.180)	-0.06050 (-3.144)

α_2	-0.01381 (-4.224)	-0.01138 (-3.546)	-0.01362 (-4.330)	-0.01153 (-3.679)	-0.01604 (-2.917)	-0.01249 (-2.164)
β_0	0.000086 (2.753)	0.000087 (2.710)	0.000078 (2.138)	0.000081 (2.175)	0.000236 (2.093)	0.000235 (2.129)
β_1	0.85661 (25.803)	0.85503 (24.995)	0.88761 (22.862)	0.88389 (22.606)	0.83540 (15.991)	0.82881 (15.943)
β_2	0.09432 (3.444)	0.09516 (3.406)	0.06571 (2.684)	0.06723 (2.752)	0.10366 (2.993)	0.11190 (3.041)
$\alpha_1 - \alpha_2$	-0.03806 (-2.267)	-0.02583 (-2.104)	-0.03668 (-2.778)	-0.02408 (-2.239)	-0.06633 (-2.498)	-0.04801 (-2.323)
Probabilities of	On $[\varepsilon_t / \sigma_t]$	On $[\varepsilon_t / \sigma_t]$	On $[\varepsilon_t / \sigma_t]$	On $[\varepsilon_t / \sigma_t]$	On $[\varepsilon_t / \sigma_t]$	On $[\varepsilon_t / \sigma_t]$
Q(12)	0.770	0.679	0.872	0.821	0.362	0.384
Q(24)	0.778	0.741	0.831	0.788	0.741	0.725
Q(36)	0.969	0.953	0.916	0.882	0.809	0.770
Probabilities of	On $[\varepsilon_t / \sigma_t]^2$	On $[\varepsilon_t / \sigma_t]^2$	On $[\varepsilon_t / \sigma_t]^2$	On $[\varepsilon_t / \sigma_t]^2$	On $[\varepsilon_t / \sigma_t]^2$	On $[\varepsilon_t / \sigma_t]^2$
Q(12)	0.912	0.892	0.598	0.512	0.999	0.999
Q(24)	0.979	0.961	0.953	0.899	0.999	0.999
Q(36)	0.965	0.959	0.920	0.882	0.999	0.999

Notes: i_t is the monthly 3-month T-Bill rate. The T-Bill rate is in percent per annum. $D3_t$ is a dummy variable that takes the value 1 if the S&P 500 > 1000, and 0 otherwise. $D1_t$ is a dummy variable that takes the value 1 in January and 0 otherwise. $D2_t$ is a dummy variable that takes the value 1 in December, January, and February, and 0 otherwise. Q(k) is the Ljung-Box Q-statistic for lag k. Only probabilities of the Q-statistics are reported. A probability that is higher than the Type I error of 0.05 is evidence of no serial correlation. T-statistics are in parenthesis. The symbol Δ is for the first-difference operator. Log is the natural logarithm.

Finally Table 4 reports the estimates of the conditional variance equations in model (9) for the three stock market indices. Volatilities are persistent but are still mean-reverting. The sum $\beta_1 + \beta_2$ is less than 1 for all six regressions, but the half lives of mean reversion show a slow mean-reverting process, ranging between 11.02 and 14.50 months.

Implications

In this section the implications of the results to traders, investors, speculators, stock exchange regulators, and policy makers are addressed to. First, the paper provides statistical evidence that the psychological traits of some traders can affect significantly stock markets. These traders are not fully rational, but can be described as having *bounded* rationality, because of their overreaction. Hence it is advisable that these traders temper their reactions to interest rate news in the winter season. Investors, however, should distrust price signals in the winter season, particularly if interest rates are volatile. Speculators can take advantage of the seasonal overreaction by buying the market in the winter when interest rates rise unexpectedly, and by selling the market in the winter when interest rates fall unexpectedly. This recommendation works out because in the winter stock prices fall (rise) by more than what is required when interest rates unexpectedly rise (fall). These transactions can take place either in the spot market or in the futures market.

In turn, regulators should not give too much importance on volatility of stock prices during the winter, because this volatility is partly due to overreaction, and because this overreaction will fade away later on. Hence regulators should try to accommodate excess volatility in the winter especially when interest rate changes are uncertain.

Policy makers can adapt to the seasonal cognitive bias that is the object of this paper by following in the winter a less restrictive policy or a less expansionary policy than what is warranted for the other months. Overreaction will ensure that this softened course of action by policy makers in the winter will have the intended outcome.

Finally, it must be noted that sometimes financial anomalies stimulate excess activity from speculators, and tend to disappear after they are discovered, unless arbitrage is risky. That is why the strategies discussed in this section may become vain. The economist needs to ascertain that the financial anomaly will endure in the future. If the future remains like the past then the strategies prescribed here are worth adopting.

Conclusion

This paper started from the observation that some individuals, estimated to be between 1.2% and 12.4% of the population in the clinical literature, and around 8% of the population in the sample size of Rastad *et al.* (2005), and who are young and educated, may suffer from SAD (Seasonal Affective Disorder), or winter depression. These individuals may even influence trading in stock markets, or at least introduce significant noise trading. The purpose of the paper is to measure whether there is indeed a cognitive bias like SAD in the reaction of the stock market to interest rate news. Three stock market indices are studied: the S&P 500, the DJIA, and the NASDAQ. The first two are large-cap stock indices, while the third one is mainly a small-cap stock index. Hence the results do not hinge on the type of stock index selected. The evidence shows clearly the presence of overreaction, especially when the S&P 500 is below the psychological barrier of 1000. Overreaction to interest rate news in winter is approximately double the effect of interest rate news that occurs in non-critical months (non-January, and non-winter). The statistics seem to favor a January effect rather than a winter effect. Nonetheless, and generally speaking, a cognitive bias, like SAD, seems to be working significantly through US financial markets.

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