Sports Sentiment and Stock Returns: The Bombay Stock Exchange

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Abstract

Problem/Relevance: This study is motivated by psychological evidence of a strong connection between sporting event outcomes and mood. To evaluate this connection, we analyze the Indian stock market reaction to sudden changes in investors' mood captured by India's cricket results. By focusing on a rarely studied mood variable and a very infrequently studied stock exchange, this study adds to our understanding of the association between sporting event outcomes and mood.

Research Objective/Questions: In this study, we investigate the impact of cricket wins and losses on the Bombay Stock Exchange. We hypothesize that cricket wins or losses will drive investors' mood substantially and unambiguously so that the game outcomes will be powerful enough to impact asset prices. We also evaluate the hypothesis that losses are psychologically more powerful than wins.

Methodology: We analyze the daily data from the Bombay Stock Exchange using the methodology of Edmonds et al. (2007). This methodology has the advantages of capturing the Bombay Stock Exchange stock returns time-varying volatility through a GARCH model.

Major Fundings: Our findings show that cricket wins and losses do not impact the Bombay Stock Exchange. On the exchange, stock prices reflect relevant information. Our results are thus consistent with the Efficient Market Hypothesis.

Implication(s): Our results imply that on the Bombay Stock Exchange, cricket wins and losses cannot be reliably used by investors and portfolio managers to achieve returns in excess of the average market returns on a risk-adjusted basis.

Keywords: Sentiment, Sports Sentiment, Investor mood, ARCH, GARCH, Bombay Stock Exchange

Introduction

Recent work in cognitive psychology suggests that mood has a significant effect on the way information is processed (Gear et al., 2017). Good mood induces optimistic behaviors while bad mood encourages pessimistic behaviors. Since optimists expect that more good (desirable) things will happen in the future than bad (undesirable) things, optimists tend to pay less attention than pessimists (Scheier and Carver, 1985). Pessimists are prone to worry and devote more time to processing information (Schwarz, 2002). The relationship between peoples' state of mind and the way they process information is called the mood-as-information theory (Bless et al., 1990).

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The mood-as-information theory explains why studies have established a relationship between investors' mood and asset prices. Shu (2010) reports a positive relationship between equity prices and investors' mood. Cohen et al., (2013) find that investors' mood on a specific day impacts NASDAQ opening prices. Au et al., (2003) establish that traders in a good mood lose money because they exhibit overconfidence and take unwarranted risks. Nofsinger (2005) shows that the market reacts faster following pessimistic news than after optimistic news.

Researchers have established the relationship between stock indices and non-economic events such as the weather (Saporoschenko, 2011), sleep patterns (Kamstra et al., 2000), seasonal affective disorder (Dolvin et al., 2009), daylight savings (Pinegar, 2002), and the position of the moon (Yuan et al., 2006).

Researchers have also established the relationship between stock indices and sporting events. Ashton et al., (2003) describe a significant relationship between the results of the English football team and the returns of the FTSE100 index on the London Stock Exchange. They report that wins are followed by favorable stock returns and losses by unfavorable returns. Edmans et al., (2007) report negative returns when the national soccer team of a country loses a game. Consistent with the theory of loss aversion, Ashton et al. (2003) explain that when the national soccer team wins, the national market does not increase. They also suggest that when the team loses, the national market decreases. As always, the reality is complex and controversial results are also reported. Demirhan's (2013) analysis of the Turkish soccer team matches from 1988-2011 shows that stock index is unaffected by wins but affected by losses of national teams. Klein et al. (2009) do not find a statistically significant relationship between the nations' stock returns and the European World Championship soccer match results.

Van Rees (2010) report the limited effect of Dutch soccer match results on the Dutch stock exchange, while Kang and Park's (2015) analysis of the Korean market indicates that the Korean soccer team only affect stock returns during the World Cup and the Asian Cup. Aygoren et al., (2008) find that matches played by Turkish Soccer clubs produce abnormal returns if those matches are played in Europe. Berument et al., (2013) report that Turkish economic agents increase their risk tolerance after soccer team wins. Botha and De Beer (2013) note that there is no correlation between national sporting events and abnormal asset returns in South Africa.

These studies show that when soccer is used, results vary according to the country analyzed. Additionally, they also show that very few studies analyze other sports. Among the few exceptions, the notable research of Edmans et al., (2007). These studies also explain the need to capture investors' mood (Beer et al., 2013).

To sum up, the empirical link between soccer matches and asset prices deserves further research since results are inconclusive and vary across different countries. Additionally, since very few studies have investigated the relationship between other sports and asset prices, studies focusing on other sports are needed as well.

In this study, we investigate the impact of cricket wins and losses on the Bombay Stock Exchange (BSE). We hypothesize that cricket wins or losses will drive investors' mood substantially and unambiguously so that the game outcomes will be powerful enough to impact asset prices. According to Guha (1998), during some cricket games "…normal life comes to a standstill, with hundreds of millions of Indians glued to their radios and television sets" (Guha, 1998, p. 158). This observation provides strong *a priori* motivation for using cricket game outcomes to capture mood changes among investors in India. It is difficult to imagine other sporting events that will produce such a substantial and correlated mood swing in a large proportion of India's population. We also suggest that the popularity of cricket justifies the hypothesis that cricket game outcomes will impact a large enough portion of the population, i.e., enough investors to impact stock prices. Finally, we also suggest that the impact of cricket wins or losses will be highly correlated across the majority of individuals.

In this paper, we examine these hypotheses using the BSE daily returns during a seven-year period beginning June 2nd, 2008 and ending on June 30th, 2015. Contrary to the Efficient Market Hypothesis (EMH)'s premise that asset prices properly reflect all information (Fama, 1998), our study assumes that in specific instances financial markets can be inefficient (Shiller, 2003; Beer et al., 2011). This paper is thus part of the literature that investigates the effect of investors' mood on asset prices (Cao & Wei, 2005).

We believe that this research has important contributions. First, it focuses on a rarely studied mood variable (cricket game results) to evaluate the relationship between investors' sentiment and asset prices. Second, it uses data from an infrequently studied exchange, the BSE. Third, previous studies on the relationship between sports and sentiment point to contradictory results. Fourth, this study is important for practitioners since the relationship between sports events and market performance has the potential to impact their ability to generate positive returns.

This paper includes four parts; the first part establishes that cricket wins and losses can be used as a mood variable and introduces the BSE. The second part presents the hypotheses, the data and the methodology. The third part discusses the results. The final part evaluates research limitations, makes suggestions for future research directions, and concludes this research.

Cricket and the Bombay Stock Exchange

Cricket

As discussed in the previous section, research in psychology has established that individuals' mood affects their decisions (Dickhaut et al., 2003, Johnson & Tversky, 1983). For soccer games, studies show that when their team wins, people feel joyful and happy. Alternatively, when their team loses they experience sadness and melancholy (Cialdini et al., 1976). Since the outcomes of soccer games impact mood, soccer is considered to be a mood variable.

To impact mood, cricket must also be considered a mood variable. A mood variable must exhibit three characteristics to impact asset prices (Edmands et al., 2007). First, the variable must affect a large enough segment of the population. Second, the influence of the event must be unambiguous in a sense that winning evokes a positive emotion and losing evokes a negative emotion. Third, the impact of the event must be highly correlated among a majority of individuals. Cricket wins and losses satisfy these three key characteristics.

First, cricket outcomes must influence the mood of a large segment of the population to impact investors and induce a market reaction. Guha (1998) report that during games, hundreds of millions of Indians are glued to their radios. The popularity of the game has grown drastically with the explosion of television ownership. In 1989, around 30 million Indian households had a television. Nowadays, when India's national team plays a game, an estimated 400 million people watch on television. Cricket is no longer an elite game; it is now a populist event. What was once commonly known as an English summer game has evolved toward a celebrity-infused, exceptionally politicized, billion-dollar industry. To sum up, since cricket outcomes have the potential to change the mood of a large enough portion of the population, cricket has the potential to impact the market.

Second, cricket outcomes drive mood substantially and unambiguously so that the game results are powerful enough to impact asset prices. Research has shown individuals strive to attach themselves to social groups that reflect positively on them. India's cricket fan-base exhibits similar characteristics. Since the popularity of the game has increased, being a known fan of the national team is viewed positively. India has won all of the International Cricket Council (ICC) Tournaments, including the ODI's World Cup twice (1983 & 2011). India's victory at the ICC World Twenty20 in 2007 and the country performance during the ICC games of 2013 has also

contributed to increasing the popularity of the sport. For Indians, winning a cricket game evokes positive emotions and losing evokes negative emotions.

Third, the impact of the mood variable must be correlated across a large number of individuals within the country. With the introduction of the Indian Premier League (IPL), people from all over the world have come to enjoy India's cricket game. India is known to have produced some of the most notable cricket athletes, including Kapil Dev, Sunil Gavaskar, Rahul Dravid and Sachin Tendulkar. Indians' affection for cricket is unfathomable. In February 2014, India granted the Bharat Ratna, its highest civilian honor, to Sachin Tendulkar. A nation of 1.3 billion individuals and just a single broadly prominent sporting event led cricket to become a nationally celebrated event.

Bombay Stock Exchange

Bombay Stock Exchange (BSE) Limited is the oldest stock exchange in Asia. The exchange history can be traced back to the 1850s when a group of five stockbrokers started to conduct meetings under a banyan tree in front of the town hall in Mumbai. As the number of stockbrokers increased, the group eventually moved to the Dalal Street, and the BSE was born. The exchange was established as "The Native Share & Stock Brokers Association" in 1875. It was the first stock exchange in the country to obtain permanent recognition from the Government of India under the Securities Contracts Act of 1956.

The BSE's long lifespan has resulted in the exchange having more than 7,152 listings and a market capitalization of more than $1.5 trillion. The largest company traded includes: Bharat Heavy Electrical (₹[1] 33189.46 Cr[2]), Bharat Petroleum (₹ 84868.4 Cr), HDFC Bank (₹ 325481.72 Cr), ICICI Bank (₹ 151788.95 Cr), INFOSYS Technologies Limited (₹ 238342.46 Cr), State Bank of India (₹ 195427.91 Cr), Tata Motors (₹ 156274.55 Cr), and Wipro Technologies (₹ 117577.45 Cr). A brief comparison between the BSE, NYSE, and NASDAQ is presented in Table 1.

Table 1. BSE, NASDAQ and NYSE

	BSE	NASDAQ	NYSE
# listed	7,152	3,211	3,155
Market cap	$1.5 trillion	$7.8 trillion	$19.6 trillion
Location	Mumbai, India	NY, United States	NY, United States
# members	1428	189	162
Established in	1875	1971	1792
Initial Fees	$425	$50,000-$125,000+	$100,000 - $150,000
Revenue	$104 million (2016)	$2.3 billion (2016)	$3.3 billion (2015)

BSE stands for the Bombay Stock Exchange, # listed is the number of companies listed and # members the number of members.

As shown, the BSE has more than twice the number of companies listed than the NYSE and NASDAQ. Nonetheless, the larger number of companies listed, the BSE market capitalization is barely 19% of the market capitalization of NASDAQ and 7.65% of the market capitalization of

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[1] ₹ denotes Indian currency Rupees

[2] Cr. = Indian numbering system, scientific notation: 10^7

the NYSE. The BSE revenues in 2016 were 104 million U.S. dollars, 20 times lower than NASDAQ and NYSE.

The SENSEX is the BSE key index. Figure 1 compares the Dow Jones[3] (DJIA) and the SENSEX daily closing value for the period starting in 2008 and ending in 2015, i.e. the period studied.
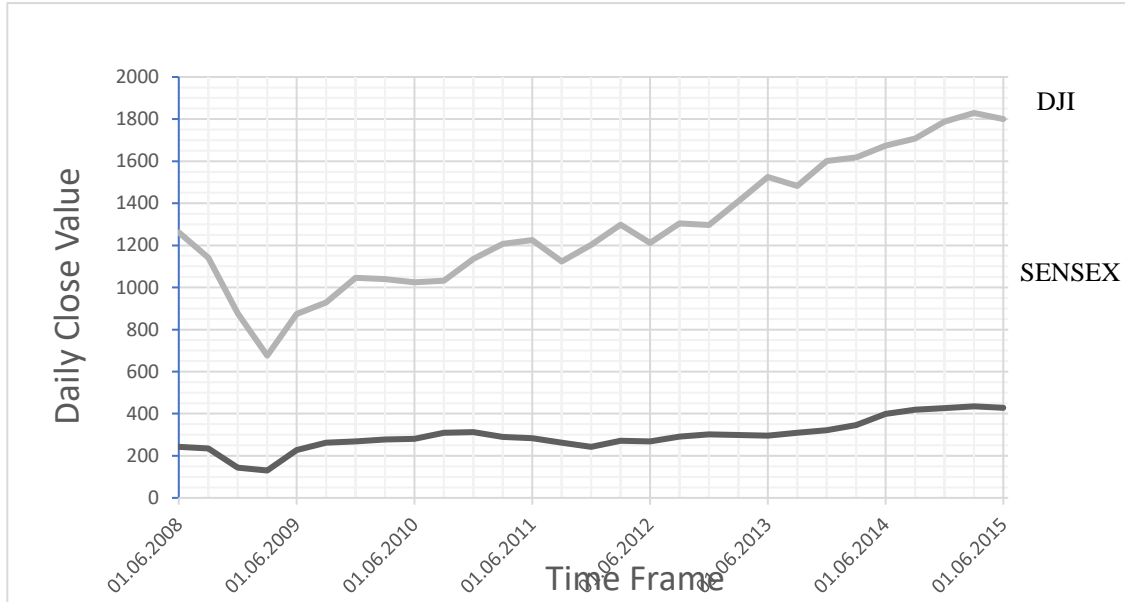
Due to the low currency exchange rate from Rupees to USD, the DJIA has been adjusted.[3]

Figure 1. SENSEX and DJIA

As shown in the graph above, the DJIA and the SENSEX exhibit a similar trend. Note however, that the DJIA decreases more than the SENSEX during the 2008 crisis. The DJIA increases faster than the SENSEX after the 2008 crisis.

Hypotheses, Data and Methodology

Hypotheses

Our null hypothesis states that the BSE is not influenced by cricket outcomes. This hypothesis implies that the BSE is efficient and that Indian investors are rational. This hypothesis runs contrary to the findings of the psychology literature that suggest fans' moods are affected by sports outcomes. The alternative hypothesis states that the BSE is impacted by cricket outcomes. The null and the alternative hypotheses are presented below:

H_0: Asset prices on the BSE are not impacted by the outcomes of cricket games.
H_1: Asset prices on the BSE are impacted by the outcomes of cricket games.

As written, the alternative hypothesis does not account for the fact that abnormal returns are more likely to be associated with losses than with wins. As discussed in the literature section of this manuscript, several studies have suggested that losses are psychologically more powerful than

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[3] Accurate representation of the DJIA is 10 times the value presented in the figure.

wins. Loss aversion was first demonstrated by Kahneman and Tversky (1984). To account for these findings, a third hypothesis is tested.

H₃: Asset prices on the BSE are impacted more by losses than by wins.

Data

Our study uses daily SENSEX data over the period from June 2nd, 2008 through June 30th, 2015. Data were obtained from CMIE Prowess[4]. The daily index returns are calculated using the standard return formula:

$$R_{BSE,t} = \ln\left(\frac{P_t}{P_{t-1}}\right) * 100 \tag{1}$$

With:

$R_{BSE,t}$	The daily returns at the end of day t.
P_t	The SENSEX index at the end of day t.
P_{t-1}	The index at the end of the previous day.
ln	The natural log.

During the seven years studied, the Indian cricket team[5] played 112 matches, winning 77 matches and losing 35 matches. Data from the matches were gathered from ESPN Sports Media Ltd[6]. In this study, we focused on weekdays only, i.e., days during which the market is open. We also only analyze wins and losses, ignoring ties.

Methodology

The three hypotheses discussed in the previous section are evaluated using a methodology similar to Edmans et al., (2007). The methodology is described below.

We start with the estimation of equation 2. Equation 2 presented below expresses $R_{BSE,t}$ as a function of variables controling for the book-to-market (HML), size (SMB), and days of the week (Day). The equation also accounts for the first order serial correlation by using the lagged index returns ($R_{BSE,t-1}$).

$$R_{BSE,t} = \beta_0 + \beta_1 R_{BSE,t-1} + \beta_2 R_{SMB,t} + \beta_3 R_{HML,t} + \beta_4 Day_M + \beta_5 Day_{Tu} + \beta_6 Day_{Th} + \beta_7 Day_F + \varepsilon_{BSE,t}$$

With: (2)

$R_{BSE,t}$	The BSE stock return in period t.
$R_{BSE,t-1}$	The BSE stock return in t-1.

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[4] CMIE Prowess is the Largest Database of Indian Companies.

[5] The data studied consists of one Cricket team called the "India national cricket team" which represents India in international matches.

[6] The results of the matches are obtained from the website http://www.espncricinfo.com/

$Day_{,M,TU,TH,F}$	A series of dummy variables that correspond to the day of the week.[7]
$R_{SMB,t}$	The return on a zero-investment portfolio that is long on small asset stocks and short on large value stocks.
$R_{HML,t}$	The return on a zero-investment portfolio that is long on high book-to-market value stocks and short on low book-to-market value stocks.
$\varepsilon_{BSE,t}$	The residuals.

Using the estimated residuals from equation 2 ($\hat{\varepsilon}_{BSE,t}$), we then evaluate the impact of the cricket outcomes using two dummy variables. The first dummy variable W_{it} equals one when India wins the game and zero otherwise. The second dummy variable L_{it} equals one when India losses the game and zero otherwise. The model is presented in equation 3.

$$\hat{\varepsilon}_{BSE,t} = \alpha_0 + \alpha_{win}W_{it} + \alpha_{Lose}L_{it} + u_{it} \qquad (3)$$

With:

W_{it}	A dummy variable that equals one when India wins the game and zero otherwise.
L_{it}	A dummy variable that equals one when India losses the game and zero otherwise.
u_{it}	The residuals.

Equation 3 is estimated using a GARCH (1,1) model to account for the fact that most stock indices exhibit time-varying volatility (Bollerslev et al., 1994). As depicted in Figure 2, this characteristic of the stock indices returns appears to be present on the BSE.
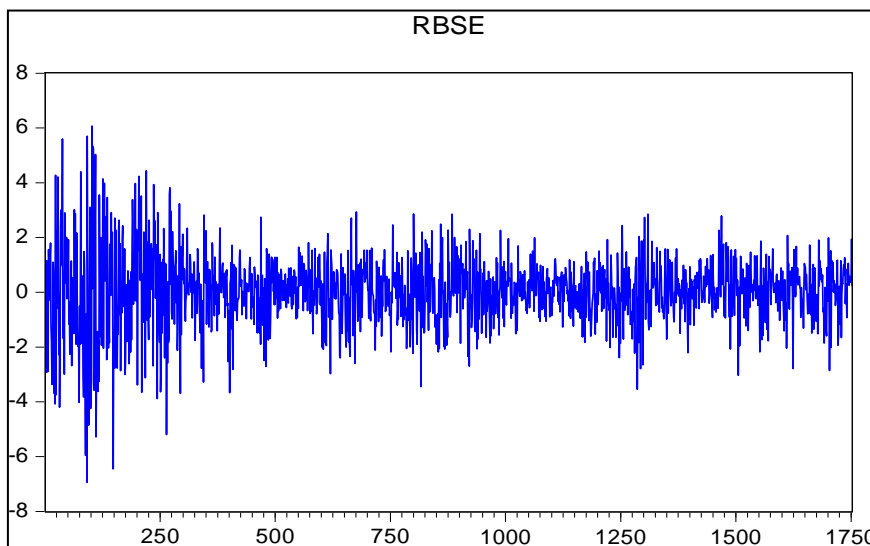

Figure 2. BSE Daily returns (RBSE)

Figure 2 shows that the BSE exhibits volatility clustering. The BSE is thus similar to other exchanges in which successive disturbances, although uncorrelated, are nonetheless serially

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[7] Notice that Wednesday is omitted from the regression to avoid the dummy variable trap.

dependent. The correlogram of squared residuals presented in Table 2 supports using a GARCH (1,1) model.

Table 2. Q-Stats

Lag	Auto Correlation	Partial Correlation
1	0.910	0.910
2	0.906	0.455
3	0.907	0.319
4	0.901	0.191
5	0.878	-0.023
6	0.880	0.069
7	0.860	-0.063
8	0.864	0.089
9	0.844	-0.046
10	0.843	0.041

The adequacy of the GARCH (1,1) model is further evaluated by the Ljung-Box test. Since adequate models are characterized by white noise residuals, i.e., identically and independently distributed residuals, *Q(m)* should be 0 for any lag *m*. As shown in Table 3 the *Q(m)* are not significantly different from zero for up to 10 lags.

Table 3. Ljung-box

Lag	Q-Stats	Probability
1	1452.3	0.000
2	2893.9	0.000
3	4338.4	0.000
4	5764.3	0.000
5	7120.6	0.000
6	8482.4	0.000
7	9784.9	0.000
8	11099	0.000
9	12354	0.000
10	13607	0.000

Accordingly, we model the volatility of the error terms from equation 2 as a GARCH (1,1) using the following:

$$\sigma^2_{BSE,t} = \theta_0 + \theta_1 \varepsilon^2_{BSE,t-1} + \theta_2 \sigma^2_{BSE,t-1} + v_t \qquad (4)$$

With:

$\sigma^2_{BSE,t}$ **The BSE index return volatility in t.**

$\sigma^2_{BSE,t-1}$ The BSE index return volatility in t-1.

$\varepsilon^2_{BSE,t-1}$ The residuals squared estimated from equation (2).

v_t The residuals.

Finally, we use the time series of estimated volatility ($\hat{\sigma}^2_{BSE,t}$) to form a new time series of normalized returns as depicted in equation 5 below. These normalized returns are then used in equation 2.

$$R^{Normalized}_{BSE,t} = \delta_{1BSE} + \delta_{2BSE}\left(\frac{1}{\hat{\sigma}^2_{BSE,t}}\right)R_{BSE,t}$$

(5)

With:

$R^{Normalized}_{BSE,t}$ The normalized BSE stock return in period t.

$R_{BSE,t}$ The BSE stock return in period t.

δ_{1BSE} & δ_{2BSE} Parameters selected so that the mean of $R^{Normalized}_{BSE,t}$ is equal to zero and the standard deviation is equal to one.

$\hat{\sigma}^2_{BSE,t}$ The BSE estimated volatility in period t.

Descriptive Statistics and Findings

The Descriptive Statistics

The descriptive statistics are summarized in Table 4. The table shows that the maximum daily returns are above 5% for all three series. It also shows that the minimum daily returns are greater than -6.9% and that the standard deviations do not exceed 1.3%. With kurtosis coefficients of 6.53 for R_{SMB}, 6.76 for $R_{HML,}$ and 5.91 for $R_{BSE,}$ the return distributions are inconsistent with the assumption of normality. The skewness coefficients which are respectively -0.219 for R_{BSE} and -0.228 for R_{SMB} suggest longer left tail distributions than the normal distribution. The positive skewness coefficient of 0.158 for R_{HML} leads to the opposite conclusion. The Jarque-Bera coefficients of 929 for R_{SMB}, 1043 for R_{HML}, and 634 for R_{BSE} all with a p<0.01 support these observations. The return distributions for these variables are inconsistent with the assumption of normality. The average return on Friday (0.028%) is lower than the average daily return on Monday (0.077%). Finally, when India participates in a cricket tournament, the average daily return reaches 13%.

Table 4. Descriptive Statistics

	Mean	Max	Min	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	Prob.	Obs.
R_{BSE}	0.0383	6.069	-6.936	1.3	-0.219	5.916	634.84	0	1380
R_{SMB}	0.0127	6.039	-4.269	0.847	-0.228	6.539	929.89	0	1380
R_{HML}	-0.002	5.449	-5.218	0.937	0.158	6.766	1043.07	0	1380
Mon	0.07700	5.69931	-5.9546	1.42348	-0.19192	5.590360	100.5737	0	352
Friday	0.02808	5.33146	-6.9362	1.33535	-0.32434	5.943054	129.4238	0	342
Game	0.13648	1.08521	0.00055	0.16868	2.953962	13.53154	680.4789	0	112

$R_{BSE,t}$ represents the BSE stock return in period t, $R_{SMB,t}$ the return on a zero-investment portfolio that is long on small asset value stocks and short on large asset value stocks, $R_{HML,t}$ the return on a zero-investment portfolio that is long on high book-to-asset value stocks and short on low book-to-asset value stocks. Std.Dev stands for the standard deviation, Prob for the probability and Obs for the number of observations.

Before we proceed further, we perform unit roots tests to evaluate whether the BSE is stationary. The stationarity of a series can strongly influence its behavior and properties. When a series is non-stationary, the persistence of stocks could be infinite. Both ADF (-37.50) and PP (-37.49) tests reject the null hypothesis of non-stationary at the 5% level.

Table 5. ADF, PP and GARCH model

Panel A.			
	R_{BSE}	R_{SMB}	R_{HML}
ADF	-37.50***	-40.603***	-36.498***
PP	-37.492	-40.606***	-36.498***

Panel B.					
	Coefficient	Std. Error	Probability	R^2	Adjusted R^2
C	0.008636	0.00284	0.0024	0.226231	0.222677
ARCH(1)	0.075816	0.01074	0		
GARCH(1)	0.916139	0.01072	0		

Akaike	Schwartz	Hannan-Quinn	Durbin Watson	Log-likelihood
2.7	2.737	2.714	1.973	2352.089

*,**,*** denotes statistically significant at 10%, 5% and 1% respectively. ADF stands for the Augmented Dickey-Fuller test, PP for the Phillips-Perron test, C for the constant variable, ARCH for the Auto Regressive Conditional Heteroscedasticity, GARCH for Generalized Auto Regressive Conditional Heteroscedasticity. The last two columns show the Ljung-Box Q-statistics and their p-values.

The Garch Model

The findings from the GARCH model are presented in Table 6. As shown in the table the R^2 and adjusted R^2 being above 22% the model adequately predicts the series volatility. The Akaike Information Criterion (AIC), Schwartz Information Criterion (SIC), Hannan-Quinn (HQ), and Log Likelihood were also calculated[8].

The coefficients of the ARCH (1) and GARCH (1,1) are all positive and significant. These positive coefficients include the estimated coefficient for the constant term in the conditional variance (θ_0), the estimated coefficient of the lag value of the square residual term (θ_1), and the estimated coefficient of the lag value of the conditional variance (θ_2).

After having appraised the suitability of the GARCH (1,1) model, we proceed with the calibration of equation 2. Results are presented in Table 6 and are divided into two panels. Panel A depicts the results using the initial returns and Panel B the results when normalized returns are used.

The regression coefficients in Panel A (the regression using the initial returns) are significant for the independent variables R_{SMB}, R_{HML}, $R_{BSE,t-1}$ and the variables representing the day of the week Monday and Friday. The coefficient for the variable R_{SMB} is negative and significant. While the coefficients for R_{HML} and $R_{BSE,t-1}$ are positive and significant. The regression coefficients in Panel B are similar. When the normalized returns are used, the coefficients for R_{SMB}, R_{HML}, and the normalized lag returns ($R_{BSE,t-1}$) are significant. The coefficient for R_{SMB} remains negative and significant, while the coefficients for R_{HML} and $R_{BSE,t-1}$ are significantly positive.

The significantly negative coefficient for R_{SMB} indicates that on the BSE, large-cap stocks outperform small-cap stocks. The positive and significant coefficient for R_{HML} implies that high book-to-market stocks (value stocks and growth stocks) outperform low book-to-market stocks.

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[8] The Akaike Information Criterion (AIC), Schwartz Information Criterion (SIC), Hannan-Quinn (HQ), and Log Likelihood are normally used to compare the goodness of fit of one model with another.

Table 6. GARCH Results

Panel A.

	Coefficient		Std. Error	R^2	Adjusted R^2
β_{0t}	0.053827	*	0.213449	0.287775	0.283557
R_{SMB}	-0.482573	***	0.023682		
R_{HML}	0.311291	***	0.017612		
$R_{BSE,t-1}$	0.135821	***	0.21868		
Monday	-0.031922	*	0.218209		
Tuesday	-0.003839	*	0.217972		
Thursday	0.011683		0.218627		
Friday	-0.035065		0.21711		

Akaike	Schwartz		Hannan-Quinn	Durbin Watson	Log-likelihood
2.723	2.757		2.736	1.719	-2374.897

Panel B.

	Coefficient		Std. Error	R^2	Adjusted R^2
β_{0t}	0.016179	*	0.139724	0.208781	0.308013
R_{SMB}	-0.009026	***	0.010605		
R_{HML}	0.010671	***	0.012532		
$R_{BSE,t-1}$	0.910443	***	0.011296		
Monday	-0.011852	*	0.141670		
Tuesday	-0.034791	*	0.141696		
Thursday	0.012322		0.141714		
Friday	-0.025873		0.141814		

Akaike	Schwartz		Hannan-Quinn	Durbin Watson	Log-likelihood
1.207	1.235		1.218	2.835	-1047.769

β_{0t} represents the constant term, R_{SMB} the return on a zero-investment portfolio that is long on small asset value stocks and short on large asset value stocks, $R_{HML,}$ the return on a zero-investment portfolio that is long on high book-to-asset value stocks and short on low book-to-asset value stocks and $R_{BSE,t-1}$ is the BSE stock return in t-1. *,**,*** denotes statistically significant at 10%, 5% and 1% respectively.

The α_{win} and α_{lose} estimates from equation 3 are presented in Table 7 which is organized similarly to the previous table, i.e., Panel A shows the results for the initial returns and Panel B for the normalized returns. In both panels the α_{win} and α_{lose} estimates are not statistically different from zero. These estimates are negative when the initial returns are used. When the GARCH (1,1) volatility adjustment and the normalized returns are used, α_{win} and α_{lose} remain insignificant, however the sign of α_{lose} is now positive.

Table 7. Wins and Losses

Panel A.			
	Coefficient	Std. Error	t-Statistic
α_{win}	-0258047	0.157947	-1.633757
α_{lose}	-0130223	0.193445	-0.673177
Panel B.			
	Coefficient	Std. Error	t-Statistic
α_{win}	-0.426187	0.128007	-3.329397
α_{lose}	0.0102831	0.170142	0.604384

α_{win} represents the return value when India wins and α_{lose} represents the return when India losses.

Conclusion

This study explores the impact of cricket wins and losses on the Bombay Stock Exchange (BSE). It is directly related to psychological research that shows how individual mood affects individual choices (Dickhaut et al., 2003). It is motivated by several factors. First, most previous studies focus on soccer. Second, the BSE is an under-researched market. Third, previous studies on the relationship between sports and sentiment point to contradictory results. Fourth, since the relationship between sporting events and market performance has the potential to impact investors' ability to generate positive returns, this study is important for investors.

We hypothesize that cricket outcomes will drive investors' mood in a sizeable and unequivocal way so that the game outcomes will sway asset prices (Hirt et al., 1992). Additionally, since numerous studies have suggested that investors react more strongly to losses than to wins, we also hypothesize that asset prices on the BSE will be impacted more by losses than by wins. These hypotheses are tested using daily data and the BSE SENSEX index for the period June 2nd, 2008 to June 30th, 2015.

The BSE series exhibits negative skewness (-0.219), high kurtosis (5.9), and a significant Jarque-Bera coefficient (634.8). Our results are thus similar to those reported by Gupta and Basu (2007). The authors show that the BSE does not display the characteristics of a random walk. As such, the market is not efficient in the weak form. The PP test performed by the authors shows that the series is stationary.

Our analysis confirms that the constant-volatility assumption is problematic because the BSE stock returns exhibit time-varying volatility (Bollerslev et al., 1994). Consequently, the effect of our standard errors could be negatively biased if any of our sampled games took place during highly volatile periods. This characteristic of the BSE is handled through a GARCH model.

Our findings show that cricket wins and losses do not impact the BSE. Further, since results for losses are inconclusive, the hypothesis of loss aversion cannot be established when the BSE is analyzed. On the BSE, cricket wins and losses do not impact prices. Our results are thus similar to those reported by Ashton et al., (2003), Gerlach, (2011), and Kaplanski and Levy, (2010).

Our results imply that on the BSE, cricket wins and losses cannot be reliably used by investors to achieve returns in excess of the average market returns on a risk-adjusted basis. When cricket wins and losses are analyzed, the BSE is efficient. Our results can also be explained by the structure of ownership of the market. While cricket is considered an important sporting event for the average Indian citizen, only a tiny percentage of Indian household savings is invested in the domestic stock market. The critical issue that holds many back from investing in the BSE is that

it is not highly liquid. As the percentage of the household investing in the market increases, the hypothesis tested in this paper should be re-evaluated. At this stage, we are concluding that cricket wins and losses do not have a pervasive impact on investors' mood. On the BSE, asset prices do not fluctuate in response to cricket-related events.

As suggested by Lee and Chiu (2016), future studies using the BSE should consider not only the market closing prices but also the market opening prices to estimate excess stock returns. In an efficient market, if a team wins or loses a game that is played during the evening, a market reaction could be detected when the market opens the following day. Future studies should also consider using individual companies. It is possible that cricket outcomes will have a significant impact on the excess stock returns of some companies but not others.

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