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AN EXAMINATION OF THE IMPACT OF INDIA'S PERFORMANCE IN ONE-DAY CRICKET INTERNATIONALS ON THE INDIAN STOCK MARKET

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ABSTRACT:

This study examines the impact of the Indian cricket team's performance in one day international cricket matches on returns on the Indian stock market. The main conclusion of the study is that there exists an asymmetric relationship between the performance of the Indian cricket team and stock returns on the Indian stock market. While a win by the Indian cricket team has no statistically significant upward impact on stock market returns, a loss generates a significant downward movement in the stock market. When Sachin Tendulker, India's most popular cricketer, plays the size of the downward movement in returns is larger.

Keywords: Cricket, India, Stock Market, Stochastic Dominance, Investor Psychology.

JEL Classification: D87, G14, L83.

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An Examination of the Impact of India's Performance in One-Day Cricket Internationals on the Indian Stock Market

INTRODUCTION

Several recent studies have focussed on the impact of sporting events on stock prices. A finding in these studies is that stock prices react sharply to team performance in big sporting events. A sporting event is a non-economic phenomenon and, as such, one might expect that stock prices will not be affected. However, behavioural finance suggests that large sporting events affect the sentiments of viewers cum investors resulting in upwards or downwards "mood swings" in the market, which are reflected in stock prices. In this study we analyse the impact of the performance of the Indian cricket team in one-day international matches on the stock market using regression analysis and the stochastic dominance (SD) method.

This study builds on a previous study by Edmans *et al.* (2007) which examined the effect of cricket match outcomes on stock market sentiment as part of a broader study considering the outcome of a range of sporting events on stock markets in several countries. This study differs from the Edmans *et al.* (2007) study in the following respects. First, Edmans *et al.* (2007) focused on World Cup matches. The World Cup is only played every four years. In this study we consider all one-day matches played by India over the period 1995 to 2005. Second, this study also makes a methodological contribution to the literature on the impact of sporting events on stock markets by using the SD method. Our focus is on India because in that country cricket, especially one-day cricket, is the number one spectator sport. When India plays in one-day internationals the whole nation comes to a standstill. A typical account of spectator interest generated by a one-day match between India and Pakistan is as follows:

> Saturday seemed to have been the start of a perfect weekend for thousands of cricket fans. After all, the wait for the ultimate clash finally drew to a close. The frenzy seemed to be well at its peak, with D-day plans being formed well in advance. The big screen experience at a restaurant, the comfort of home, the neighbourhood grocery shop, or the good old radio set, every one seemed to have worked out an arrangement to suit their need. Of course, it was no surprise that the streets bore a deserted look for most of the day (*Times of India*, Delhi Edition, 14 March 2004).

The rest of the study is organised as follows. The next section reviews the existing literature that has examined the effect of various sporting events on stock prices. We proceed to present the econometric methodology used to analyse the performance of the Indian cricket team in one-day internationals on the Indian stock market and present the results of our analysis. The final section contains the main conclusions and suggestions for further research.

EXISTING LITERATURE

Studying the impact of sporting events on the performance of the stock market is a relatively new development in the finance literature, but it forms a strand of a larger literature in behavioural finance, which studies the impacts of events that can change the mood of investors, with a subsequent effect on stock prices. The basic idea behind these studies is that after major victories in a sporting event people feel more optimistic about their chances of making a good investment or purchase, and this optimism is reflected in the relevant market. Hirt et al. (1992) found that a group of Indiana University college students who watched their college basketball team win estimated their own performance in various domains involving physical, mental and social skills to be significantly better than a group of students who watched their team lose. Wann et al. (1994) suggested that fans often feel a positive reaction when they see their team winning and a negative reaction when they see their team losing and this positive/negative reaction effects their perceptions. A study by Arkes et al. (1988) found that there was an increase in the sales of the Ohio State Lottery in the days following a football victory by Ohio State University. Petty et al. (1991) and Wright and Bower (1992) explained this behaviour by suggesting that people who are in a buoyant mood following a victory by their sports team are more optimistic about their judgement, compared to people who are in a dispirited mood following a loss by their sports team.

Studies of investor psychology have not only examined the outcome of sporting contests on investor moods, but have looked at various other events that have an impact on investor sentiment. Studies by Saunders (1993) and Hirshleifer and Shumway (2003) found that sunshine directly affects stock returns with a bright sunny morning being associated with a positive return on the stock market, while a gloomy morning was associated with a negative return on the stock market. In a similar study, Frieder and Subrahmanyam (2004) found abnormally positive returns around the Yom Kippur and St. Patrick’s Day holidays. A detailed literature review of various theories of investor psychology and asset pricing is contained in Hirshleifer (2001). In the remainder of this section we focus on studies that have analysed stock market reaction to sporting events.

There are only a few studies which have empirically analysed the effect of sporting events on the stock market. Krueger and Kennedy (1990) analysed the impact of the Super Bowl results on the New York Stock Exchange and found that the results of the Super Bowl was an accurate predictor of the stock market. Worthington (2007) analysed the impact of the Melbourne Cup (one of the southern hemisphere’s premier horse races, which is run in the first Tuesday in November) on returns on the Australian Stock Exchange and found that mean Melbourne Cup day returns were significantly higher than returns on other Tuesdays in November and that of Tuesdays in other months.

Berman et al. (2000) examined whether the announcement that Sydney had won the 2000 Olympics had any effect on the Australian stock market. They used index and individual stock level data and concluded that this news only affected the stocks of companies based in New South Wales, the host state for the Olympic Games. In a related study Veraros et al. (2004) analysed the impact of the news that Athens had won the right to host the 2004 Olympics on the Athens and Milan stock markets and found that the announcement had a statistically significant impact on the Athens stock exchange in general and on the stocks of infrastructure-related industries in particular. However, they found that the announcement had no impact on returns on the Milan stock exchange.

Ashton et al. (2003) examined the impact of the performance of the England football team on the FTSE 100 index based on all matches played by the team from January 1984 to July 2002 and found that good performances by the national football team was followed by good performances in market returns. They speculated that there could be two reasons for this result. “First, there may be a ‘feel-good’ factor with national sporting success engendering greater confidence about the future. Second, given the increasing commercial importance of international tournament finals, an efficient stock market will revise expectations of the potential economic benefits to be derived from national team performance in the light of individual match results and the likelihood of the team progressing further in the tournament” (Ashton et al., 2003, p.783).

The most comprehensive study is by Edmans et al. (2007) who analysed the impact of international football matches on the stock market of 39 countries by using 30 years of data on major football events and found the existence of a strong negative stock market reaction to losses by the national football team. However they did not find any corresponding reaction to wins by the national team. This study also looked at data for cricket, rugby, ice hockey and basketball and their results were robust across sports. The authors suggested the reason for this asymmetric behaviour is that people tend to put more weight on losses in their utility function. Hence, when their team loses, they become more dejected compared to the feeling of elation that they experience when their team wins. Another possible explanation for the observed asymmetric behaviour is that most of the football matches in the sample were elimination games, such that a win only advanced the team to the next stage of the tournament, whereas a loss eliminated the team from competition altogether.

Boyle and Walter (2003) examined the effect of performance of New Zealand's rugby team on its stock market. This is the only study that has found no systematic relationship between the outcome of a sporting event and stock market returns. The authors found this result to be robust to the time period of analysis and the frequency of the data used. A possible explanation for this finding, as suggested by the authors, is that investors are more self aware of the change in their emotional state when affected by feelings arising from success or failure in sporting events compared with emotional changes arising by events such as weather changes. When investors are more aware of their emotional changes, they are better positioned to resist irrational behaviour.

CONCEPTUAL FRAMEWORK

The basic conceptual framework draws on the psychology literature which examines the impact of mood fluctuations on the decision-making process. The economic research in this field is relatively new and is based on the idea of importing insights from psychology to explain the economic anomalies observed in real life data (such as economically inconsistent behaviour of buying insurance or lottery tickets). The pioneers of this line of research in behavioural economics and behavioural finance use the term *neuroeconomics* to refer to the science of using brain activity (such as brain imaging and other techniques) to infer details about how the brain works; and then using these details to explain economic decision-making (see Camerer et al. 2005 for more details and the basic foundation of this stream of research).

One stream of the neuroeconomics literature that is directly relevant to the aims of this study is the impact of mood on assessment of risk and long-term cost benefit calculations of individuals. Using the basics of the workings of the human brain as presented in Camerer et al. (2005) and using the descriptive “risk as feelings” model presented in Loewenstein (2000) and Loewenstein et al. (2001), the main conceptual framework underlying this study can be presented in the following descriptive model.

The human brain has four lobes. From front to back these are known as *frontal, parietal, occipital* and *temporal.* These four lobes of the brain perform four different functions. The frontal lobe is the locus of planning, cognitive control and integration of cross-brain input. The parietal lobe governs motor action. The occipital lobe is where visual processing occurs. The temporal lobe controls memory, recognition and emotion. While these different parts of the brain have different functions, neurons from different areas are interconnected in order to enable the brain to respond to complex stimuli in an integrated manner. The three features of human brain function, which play a notable role in decision making, are *automaticity, modularity* and *sense-making.* Automaticity refers to the fact that some of the brain’s activities are automatic, parallel, rapid processes which typically occur without awareness. Modularity refers to the fact that the human brain is organised in terms of various functional modules capable of working both cooperatively and independently. However, most complex economic decisions (e.g. whether to buy or sell stocks) require collaboration among these specialised modules and functions. These interactions among the various modules help explain many of the observed (and sometimes seemingly non-rational) anomalies in human behaviour. If all economic decisions are made by the frontal lobe of the brain (specialising in cognitive control), than all decisions will confirm to the rational utility maximiser's assumption. However, because of the interaction between the frontal and temporal lobes (specialising in memory and emotions), an economic decision will not only depend on cognitive analysis, but also on the emotional state of the individual.

There are many studies in the psychology literature which have found that people in a good mood make optimistic judgments and choices and that people in a bad mood make pessimistic judgements and choices. One such study is Isen et al. (1978), which found that putting people in a good mood at the beginning of an experiment (by giving them a small gift) resulted in them giving more favourable evaluations of their shopping experience than people in a neutral mood. A similar result was reached by Johnson and Tversky (1983) who found that people who read newspaper articles containing "sad" news subsequently gave higher risk estimates for a variety of potential causes of death (e.g. floods and disease) than people who read newspaper articles containing "happy" news.

While studies indicate that people feel optimistic after good news and pessimistic after bad news, the effect may not be symmetric. A study by Kahneman and Tversky (1979) suggested that the pain of loss is stronger than the pleasure of equal-sized gains. Brain imaging studies conducted by Camerer et al. (1993) and Smith and Dickhaut (2002) suggested that gains and losses are fundamentally different as there are differences in the areas of the brain that are active during gain and loss. In a related study, Dickhaut et al. (2003) found evidence of more activity in the orbitofrontal cortex of the brain when a person thinks about gains, whereas more activity was observed in the inferior parietal and cerebellar areas of the brain when a person thinks about losses.

The implications of this descriptive model for our study are straightforward. We expect that when a spectator cum investor watches his cricket team win an international one-day cricket match he will feel optimistic about his prospects and hence end up purchasing more (or selling less) stocks than he would have otherwise done. Similarly if a spectator cum investor watches his team lose an international one-day match he will feel pessimistic and hence end up selling more (or buying less) stocks than what otherwise would have been the case based on a cognitive analysis of the stock market. Because a one-day cricket match is such a substantial event in India and affects the mood of so many people, the optimism or pessimism caused by the result of the game may be large enough to make the market swing in an upward or downward direction reflecting the mood of the nation. However, market swings may not be symmetric in size. As people put a bigger emphasis on losses, the downward movement in the market following a loss should be much larger than an upward swing following a victory.

DATA AND METHDOLOGY

The stock market data for this study is taken from India's largest stock exchange, the National Stock Exchange (NSE), (www.nseindia.com). We downloaded the daily closing price data for the main index, the CNX Nifty, for the period 1995 to 2005. The daily index returns were calculated using the following standard formula:

$$R_t = \ln(P_t / P_{t-1}) \times 100 .$$

The data on one-day cricket matches was collected from www.testmatchstats.com. This website maintains a database of all international cricket matches played between the major cricket-playing nations. The nature of the game makes cricket very different from other sports such as football or rugby. While these matches are played for a short duration ranging from less than an hour to a maximum of a few hours, cricket is played for at least one whole day. Traditionally there have been two major forms of cricket: one-day matches where each side has 50 overs and test matches where each side has two innings played over five days. Another form of cricket is Twenty-Twenty, where each team bowls 20 overs in a match that lasts for around half a day. These matches, however, are a much more recent phenomenon and, over the period of the study, were a relatively uncommon phenomenon at the international level.

In the current study we only use data on one-day international cricket matches. The reason is that ascertaining the effect of test match results on stock market performance can be ambiguous, given that most test matches are played over five days and the fortunes of a team can vary over that five-day period. Another reason for focusing on one-day matches is that in India they have become more popular than the traditional test matches, because one-day cricket is played for a shorter duration and is generally regarded as being more exciting. In order to measure the impact of team performance on stock returns we use the stock market index on the first day following the game. This is to ensure that the game results are known before trading begins so we have the full one-day (close to close) returns, reflecting the results incorporated in prices.

We use two different methodologies to analyse the data. The first methodology is the standard event study model (i.e. dummy variable regression) and the second methodology is the SD approach proposed by Davidson and Duclos (2000). The rationale for using two different methodologies in the one study is threefold. First, the use of two different methodologies acts as a robustness check for the results. Second, previous studies of this sort have employed dummy regression models so using this approach in this study facilitates comparison with previous studies. Third, the stochastic dominance method is less restrictive than the dummy variable regression model because of the fact that it does not make any assumption about the distribution of the returns. In the following subsections we will briefly describe each of the methodologies.

Dummy Variable Regression Model

The standard event study analysis model entails calculating the mean index after a particular sporting event (i.e. a one-day match in which the Indian team won or a one-day match in which the Indian team lost). Once the mean returns are calculated one can compare these mean returns with the unconditional mean return on all trading days. In order to check the statistical significance of the results one can use either the standard *t*-test (assuming the returns follow a normal distribution) or a more advanced non-parametric test such as the Mann-Whitney U test or the Kruskal-Wallis H Test.

Another more efficient method to separate the effects of different events on the stock market is employing a dummy variable regression model, which is the approach we have used in the current study, after doing the above tests at the preliminary stage. To begin with we specify the following regression model:

$$R_t = \beta_0 + \beta_W W_t + \beta_L L_t + \varepsilon_t \qquad (1)$$

where R_t represents the log return for the market index and W_t and L_t are the dummy variables indicating whether India wins or loses the one-day international cricket match. Matches that are drawn, tied or abandoned (due to rain or some other factor) are treated as the control group. Given the fact that stock market data is often characterised by autocorrelation and heteroskedasticity, we used a Generalised Method of Moments (GMM) estimator to estimate the regression model.

Test for Stochastic Dominance

Stochastic dominance entails comparing two distributions and deciding which one is preferred over the other, depending upon the utility function of the agent. The stochastic dominance methodology is not confined to the field of finance but is also widely used in development economics for comparing one income distribution with the other, depending upon the utility function of the social planner. More specifically in the context of the current model, the SD method can be used to compare the distribution of two return series. The two natural ways of comparing any two return distributions are either by the level of returns (mean returns) or by the dispersion of returns (variance). These two approaches to comparing the return distributions form the basis of first-order stochastic dominance and second-order stochastic dominance, respectively. Sometimes, when the first two moments are not sufficient to ascertain the superiority of one distribution over the other, researchers have used third or higher order moments, which form the basis of third or higher order stochastic dominance.

Stochastic dominance imposes very minimalist assumptions on the utility function of investors. First-order stochastic dominance (FSD) assumes the presence of the non-satiation[1] condition in the utility function of the investor. Second-order stochastic dominance (SSD) assumes that investors are risk averse[2] and third-order stochastic dominance (TSD) assumes that an investor prefers a more positively skewed distribution. Suppose there are two return distributions denoted as *F(.)* and *G(.)* and their corresponding cumulative distribution functions(CDF) are denoted as $F_1(x)$ and $G_1(x)$ respectively. The various orders of stochastic dominance can be stated:

1. *A return distribution F(.) first-order stochastically dominates another return distribution G(.) if and only if* $F_1(x) \leq G_1(x)$ *for all values of x, with strict inequality for some (at least one) value(s) of x.*

2. *For any two return distributions F(.) and G(.) with the same mean, F(.) dominates by second-order stochastic dominance if and only if* $F_2(x) \leq G_2(x)$ *for all values of x, with strict inequality for some (at least one) value(s) of x.*

3. *The return distribution F(.) dominates G(.) by third-order stochastic dominance if and only if $F_3(x) \leq G_3(x)$ for all values of x, with strict inequality for some (at least one) value(s) of x.*

The orders of stochastic dominance follow a hierarchical process, i.e. FSD implies SSD and SSD implies TSD, but the converse is not true. We use the Davidson and Duclos (2000) test, which is regarded as the most powerful test for stochastic dominance (Tse and Zhang, 2004; Lean et al., 2007). To explain the Davidson and Duclos (2000) test suppose (y_i, z_i) are observations drawn from a population of two different kinds of returns (e.g returns following a day on which there was a cricket match and returns following a day on which there was no cricket match), such that their CDF are given by *Y(x)* and *Z(x)*. For a pre-specified grid of points, Davidson and Duclos (2000) considered the following sample statistics:

$$\hat{D}_Y^s(x) = \frac{1}{N(s-1)!} \sum_{i=1}^{N} (x - y_i)_+^{s-1} \qquad (2)$$

$$\hat{D}_Z^s(x) = \frac{1}{N(s-1)!} \sum_{i=1}^{N} (x - z_i)_+^{s-1} \qquad (3)$$

$$\hat{V}_Y^s(x) = \frac{1}{N} \left[\frac{1}{((s-1)!)^2} \frac{1}{N} \sum_{i=1}^{N} (x - y_i)_+^{2(s-1)} - \hat{D}_Y^s(x)^2 \right] \qquad (4)$$

$$\hat{V}_Z^s(x) = \frac{1}{N} \left[\frac{1}{((s-1)!)^2} \frac{1}{N} \sum_{i=1}^{N} (x - z_i)_+^{2(s-1)} - \hat{D}_Z^s(x)^2 \right] \qquad (5)$$

$$\hat{V}_{YZ}^s(x) = \frac{1}{N} \left[\frac{1}{((s-1)!)^2} \frac{1}{N} \sum_{i=1}^{N} (x - y_i)_+^{(s-1)} (x - z_i)_+^{(s-1)} - \hat{D}_Y^s(x) \hat{D}_Z^s(x) \right] \qquad (6)$$

and proposed normalised statistics as follows:

$$T^s(x) = \frac{\hat{D}_Y^s(x) - \hat{D}_Z^s(x)}{\sqrt{\hat{V}^s(x)}} \tag{7}$$

where

$$\hat{V}^s(x) = \hat{V}_Y^s(x) + \hat{V}_Z^s(x) - 2\hat{V}_{YZ}^s(x) \tag{8}$$

Davidson and Duclos (2000) showed that under $\mathrm{H}_0 : \hat{D}_Y^s(x) - \hat{D}_Z^s(x), T^s(x)$ follows a standard normal distribution. In our case, given the nature of the data, $N_Y \neq N_Z$, when observations are independently drawn from two populations, the $\hat{V}^s(x)$ can be computed as $\hat{V}_Y^s(x) + \hat{V}_Z^s(x)$ and asymptotic normality still holds (Tse and Zhang, 2004).

Ideally the null hypothesis should be tested for the full range of distributions; however, this is empirically not feasible. Bishop et al. (1992) suggested a compromise strategy of testing H_0 for a selected finite number of values of *x*. Using these pre-designed finite values of $x\ (x_1, x_2, \ldots\ldots\ldots x_K)$ and the corresponding $T^S(x_i)$, statistics, the following null and alternative hypotheses can be defined:

$$H_0 : D_Y^s(x_i) = D_Z^s(x_i) \text{ for all } x_i$$
$$H_A : D_Y^s(x_i) \neq D_Z^s(x_i) \text{ for some } x_i$$
$$H_{A1} : Y \succ_s Z$$
$$H_{A2} : Z \succ_s Y$$

The overall null hypothesis is the logical intersection of several hypotheses (one for each *x*) and the overall alternative hypothesis is the logical union of the corresponding alternative hypothesis. Bishop et al. (1992), suggested that the overall null hypothesis follows a studentised maximum modulus statistic with K and infinite degrees of freedom, denoted by M_∞^K. The studentised maximum modulus distribution with K degrees at $\alpha\%$ level of significance (denoted by $M^{K}_{\infty,\alpha}$) is used to control the probability of rejecting the null hypothesis. As tabulated in Stoline and Ury (1979), the following decision rules based on $1-\alpha$ percentile of $M^{K}_{\infty,\alpha}$ can be used:

If $|T_s(x_i)| < M^{K}_{\infty,\alpha}$ for $i = 1,......,K$ accept H_0.
If $T_s(x_i) < M^{K}_{\infty,\alpha}$ for all i and $-T_s(x_i) > M^{K}_{\infty,\alpha}$ for some i accept H_{A1}.
If $-T_s(x_i) < M^{K}_{\infty,\alpha}$ for all i and $T_s(x_i) > M^{K}_{\infty,\alpha}$ for some i accept H_{A2}.
If $T_s(x_i) > M^{K}_{\infty,\alpha}$ for all i and $-T_s(x_i) > M^{K}_{\infty,\alpha}$ for some i accept H_A.

Here, it is to be noted that H_A is exclusive to both H_{A1} and H_{A2}; that is, if the test accepts H_{A1} or H_{A2}, it will not be classified as H_A. H_A is accepted only when $Y(x) < Z(x)$ for some x and $Z(x) > Y(x)$ for some x. So, if H_0 or H_A is accepted, there is no stochastic dominance of one distribution over the other (e.g. the distribution of returns on days following cricket matches over returns on days that do not follow cricket matches). On the other hand if H_{A1} or H_{A2} is accepted at the first order than one distribution stochastically dominates the other distribution at the first order. Acceptance of H_{A1} or H_{A2} for the second or third order can be interpreted in a similar fashion.

RESULTS

As the first step of our analysis we calculated the summary statistics for the data. Table 1 presents the mean returns, standard deviation, skewness, Kurtosis and Kolmogorov-Smirnov (K-S) test statistics on the day after a cricket match, categorised according to the type of one-day match in which India played. The data shows that mean returns on days following a cricket match in which India lost are lower than the mean returns on days following a match in which India won or days in which there was no match.

From 1995 to 2005 the Indian cricket team won 143 one-day international cricket matches and the average return after these matches was -0.032. In the 131 matches India lost over this decade the average returns on the following day was -0.231, roughly seven times lower than the winning day mean returns. The returns after losing a match in India were around eight times lower than the returns after winning a match in India, while the returns after losing a match in a country other than India were around six times lower than the returns after winning a match in a country other than India.

Examining the higher order moments in Table 1 we observe that the standard deviation of returns is quite high compared to the mean returns, suggesting that large dispersion is present in the data. The high dispersions or volatility in financial returns is a commonly observed phenomena and could have been caused by various market or non-market factors which are not the focus of the current study. The high value of Kurtosis and significant K-S test statistics for some cases in the last two columns of Table 1 indicate that the returns distribution differs significantly from the normal distribution. This result further justifies the use of the Davidson and Duclos (2000) SD method for the main analysis, as this method does not make any assumption about the distribution of returns.

Table 2 presents the summary statistics for the returns categorised on the basis of matches played with India’s opponents in one-day international cricket. The rationale for tabulating the summary statistics based on major opponents is the fact that some nations are regarded as more prominent archrivals than others in the Indian psyche, and winning or losing a match against a prominent archrival might be expected to have a greater positive or negative impact on the stock market compared to other teams. India and Pakistan have one of the strongest rivalries in international cricket. Since partition India and Pakistan have continually been involved in some form of political or military tension. This tension is manifested in cricket matches played between the two countries. Another reason for distinguishing between opponents is that the International Cricket Council (ICC) compiles a ranking of nations. The Indian cricket team was lower in these rankings than Australia, which was ranked first. One might expect that cricket fans would not be hopeful of an Indian win against Australia. Thus a loss to Australia may not have as big a negative impact on investor sentiment as a win, while if India wins a match against Australia it may have a large positive impact. The reverse is true for the cricket minnows such as Bangladesh or Kenya. Most Indian cricket fans would expect India to beat these countries so a win may have little positive effect on investor sentiment, while a loss may have a big negative effect on the stock market.

The results in Table 2 confirm the results from Table 1. There is a clear-cut difference between winning and losing matches. The mean returns on the Nifty index, after losing a match against any opponent is much lower than the mean returns after winning a match against the same opponent. In some cases, such as in matches against England and New Zealand, this difference is relatively large and significant. However, there is no sizeable difference between winning and losing returns for cricket matches played against Pakistan. As discussed earlier, one might expect a bigger difference in matches played against Pakistan because of the intense rivalries between the two countries. One possible explanation for the result is that over the period of the study India and Pakistan were of roughly similar standing in terms of strength, meaning Indian fans anticipated the chance of each team winning or losing the match with an equal probability. Thus, if India loses against Pakistan, the result is not totally unanticipated.

While the main conclusions of this study are based on the Davidson and Duclos (2000) SD test, as a first step we started with the dummy variable regression model. The results of the dummy variable regression model are reported in Table 3. We estimated the regression model given in Equation (1), using the GMM estimation technique. In order to capture the potential asymmetric effects of winning and losing cricket matches, we used separate dummies for winning and losing. Thus a dummy variable W_t takes a value of one on the day following a match India won and a value of zero otherwise. Similarly the variable L_t takes a value of one on the day following India losing a match and takes a value of zero otherwise. There were some matches for which no team won or lost (such as drawn matches or matches abandoned because of inclement weather). For these matches both dummies take a value of zero. Examining the results of the dummy variable regression in Table 3, we observe that there is definitely a negative asymmetric impact of winning and losing matches. We see that the coefficients for the loss dummy are negative and significant for most cases, whereas the win dummy, although positive in all cases, is never significant. Looking at the data for all matches we see that losing a match in general (no matter against whom or whether in India or overseas) has a significantly negative impact on the stock market, whereas winning a match has a positive, albeit not significant, impact on the stock market. We also re-estimated the first regression after introducing a location dummy variable which took a value of one for matches played in India and zero otherwise; however, it was not significant and it did not affect the sign or significance of the other dummy variables.

The next issue we examined through a dummy variable regression model was whether there is a Tendulkar effect present in the data. Sachin Tendulkar is arguably the world's best batsman and is the most popular cricket player in India. One would expect that if Tendulkar was playing, Indian cricket fans would be more optimistic of an Indian win than if Tendulkar was not playing. We hypothesise that if India loses when Tendulkar is playing this will be a bigger setback to the Indian fans compared to the case when India loses in the absence of Tendulkar. In order to examine whether there is a Tendulkar effect we run a regression by separating the matches in which Tendulkar played and India lost and the matches in which

Tendulkar played and India won. From 1995 to 2005 there were 118 matches in which Tendulkar played and India won the match while there were 100 matches in which Tendulkar played and India lost the match. The coefficient on the loss dummy become even more negative (the magnitude increases by roughly 33%) and remains significant at the 5% level. However, the win dummy variable still remains statistically insignificant.

We also ran separate regressions for the subset of matches played as part of the World Cup or the finals of regular tournaments, such as the Asia Cup, the Champions Trophy, the Sharjah Cup or the ICC Knockout Trophy. The rationale is that such matches are more likely to generate bigger mood swings because more hinges on the outcome. There were 51 of these special tournament matches; of which India won 25 and lost 26 matches. In the regression results for these matches we also found that the loss dummy is negative and significant (with a slightly higher magnitude) whereas the win dummy remains insignificant. We also ran separate regressions for India’s major opponents. While the results for separate opponents are consistent with the earlier results, some aspects of the results are worth noting. We were expecting a significant result for matches against Pakistan, but the coefficients on the Pakistan dummy variables were insignificant. Moreover, surprisingly we found highly significant coefficients on the loss dummy for England, Kenya and New Zealand, none of which is generally considered to be a close rival of India. The case of Kenya is understandable as Kenya is ranked much lower than the Indian cricket team and a loss to Kenya is definitely a big setback to Indian fans. The reason why many results were insignificant when we ran regressions on an opponent by opponent basis could be the small number of observations.

The regression framework assumes that the data is normally distributed, while the returns in this study exhibit significant deviation from a normal distribution. Thus, we also employed the SD approach which does not make any assumption about the distribution of the returns. Another limitation of the regression approach is that it does not tell us whether the investor's preference between portfolios will lead to an increase in wealth or, in the case of risk-averse individuals, whether their preference will increase utility without an increase in wealth. The SD approach can make these distinctions clear and bring out a better picture of investor preference for one distribution of returns over another. To make a visual comparison of the distribution of returns, we plot the CDF corresponding to various categories of days following a cricket match and days not following a cricket match in Figure 1(a), (b) and (c). Figure 1(a) presents the CDF of returns following matches India lost over the CDF of non-cricket playing days returns. We see that for most of the distribution the non-cricket days distribution dominates those days following an Indian loss; however, the two distributions exhibit occasional crossing towards both ends. A similar picture emerges from the other two CDF plots; namely, Figure 1(b) where we plot the CDF of returns on days following an Indian win with the CDF of returns on days following an Indian loss, and in Figure 1(c) where we plot the CDF of returns on days following an Indian win in which Tendulkar played compared to the CDF of matches in which Tendulkar played but India lost. In all the cases we observe that the distribution of returns on the day following an Indian loss is dominated by the other distribution (days following an Indian win or non-match days); however, in each case we observe that the two distributions cross each other at a few points, thus implying that none of the distribution has FSD over the other distribution. This preliminary graphical analysis conducted using the CDF plots suggests that we may not observe any FSD results while conducting the formal SD test, because the return distributions cross each other.

We apply the DD test to compare the distribution of returns that cross each other. Here it is to be noted that the DD test rejects the null hypothesis if none of the DD statistics is significantly positive and at least one of the DD statistics is significantly negative (Davidson and Duclos, 2000). As indicated by Leshno and Levy (2002), in some situations X dominates Y in a small range, but most risk-averse individuals prefer Y to X, a situation termed as "almost stochastic dominance", generally not captured by the DD test, due to its restrictive decision rules. So in order to overcome the restrictions imposed by the DD test's restrictive decision rule and to minimise committing the chances of a Type 2 error (of finding dominance when there is none), we used a 5% cut off point, i.e. a particular distribution is said to dominate the others if at least 5% of the T_s are significantly negative and no portion of T_s is significantly positive.

Figures 2(a) to 2(d) graphically demonstrate the values of the first three orders of DD statistics for various combinations of return distribution for which we conducted the DD test. A common pattern observed in the DD statistics in all the plots is that first-order DD statistics, T1, move from negative to positive along the distribution of the returns (except for case 2(b) where it moves from negative to positive but than again quickly becomes negative). This implies that starting from the lower range of the distribution to up to almost three-quarters of the return distribution, the returns on days following a day in which India did not lose (i.e. India won or there was no match) the distribution of returns dominate the returns on a day following an Indian loss. However this domination is not maintained over the remaining upper quartile of the returns. Comparing returns on days after India won with returns on days after India lost (i.e. ignoring all the non-cricket days) we see that returns on days following an Indian win FSD returns on days following an Indian loss for almost the whole distribution except for a small negative range in the distribution of returns. We also observe that in all the four plots the second-order DD statistics and third-order DD statistics (i.e. T2 and T3) consistently remain negative over the entire distribution of returns. This indicates second and higher order dominance of the returns following a day in which India did not lose over returns on a day in which India lost.

Table 4 summarises dominance among different return distributions depending upon the outcomes of various cricketing days. One result that stands out very clearly is that losing a cricket match has a stronger negative impact than the positive impact of a winning a match. In all the comparisons we see that the returns after winning a match TSD returns after a non-match day (see tests 2, 6 and 9 in Table 4). However, when we compare the non-match days with the returns on a day following an Indian loss we see that the nature of stochastic dominance improves by an order and we observe a SSD i.e. the non-match days SSD days following an Indian loss (tests 3, 7 and 11 in Table 4). The results do not become any clearer when we directly compare the distribution of returns on the day following an Indian win with the distribution of returns on a day following an Indian loss. Returns on the day following a win dominate returns on a day following a loss by a second order of dominance (tests 4, 8, 11 and 14), suggesting that, compared to the return on a day following an Indian loss the return on a day following an Indian win is no better than the average return of a non-match day.

CONCLUSIONS

In the current study we examined the effect of the performance of the Indian cricket team in one-day internationals on the main market index (Nifty Index) from the NSE. We used two different methodologies to ensure the robustness of results. The traditional regressions analysis was performed using the GMM framework, in order to take account of the problems of heteroskedastcity and autocorrelation which are generally present in financial data. The second method involved empirically testing for stochastic dominance using the DD-test proposed by Davidson and Duclos (2000).

The results obtained using both regression analysis and the stochastic dominance method suggested that the performance of the Indian cricket team in one-day matches strongly affects the Indian stock market. The nature of this impact was found to be asymmetric i.e. a victory by the Indian cricket team does not have a large positive impact on the stock market but the defeat of the Indian team does have a relatively large negative impact on the Indian stock market. This negative impact increases in magnitude when India loses a match in which Tendulkar, the most popular cricketer in India, plays. The SD analysis indicated that the impact of winning matches is not completely insignificant; the distribution of returns after winning matches was found to weakly dominate (of order 3) the distribution of normal non-match returns. The asymmetric result obtained in the analysis is consistent with the view that people value losses differently from gains. The results suggest that the wave of optimism introduced by a win is not as big in magnitude as the wave of pessimism following a loss.

An extension of this work could be to study market movements in terms of the amount of trading activity registered on the exchange (measured by the volume or number of transactions), in response to a cricket match (especially the ones played on a weekday). Such a study might be able to give an estimate of the business activity foregone on the Indian stock market, due to the fact that investor’s attention was occupied with cricket matches. This line of research can also be used to examine the effect of the outcome of cricket matches, or the performance of specific superstars, on stock market outcomes in other countries. One could, for instance, examine the presence and performance of Sir Donald Bradman on the Australian stock market in the 1930s and 1940s. Bradman, whose career lasted from 1927 to 1949 seasons and who still maintains the world record of the highest test match average of 99.94 runs, is widely regarded as the greatest ever Test cricketer and an icon of Australian sport. One study has estimated that attendance at Test Matches increased by 7,000 each day he batted and that this translated to $65,000 in daily additional revenue (in contemporary

Australian Dollars) (Blackham and Chapman, 2004). Using long time-series data for Australian stock prices and data on when Bradman played together with his performance one could test for the possible presence of a Bradman effect on the Australian stock market.

One limitation of this study, due to the fact that it relied on non-experimental secondary level data, has been that we have adopted a broad generalisation of the mood variable. We considered that all “mood swings” are either negative or positive deviations from some baseline mood and will have an upward or downward effect on the stock market. In a more realistic psychological setting one may expect that the mood deviation from the baseline in a negative direction might take several different forms. For example, if a team loses, supporters may experience a range of negative emotions, including sadness, disappointment, anger or frustration. While all these are negative deviations, each may have a different behavioural consequence when it comes to making an investment decision. For example, a feeling of sadness might make investors withdraw from the world (and the stock market, thus resulting in reduced trading) for a while whereas anger might make them behave in an impulsive manner which might involve selling of a lot of the stocks. These different mood variations can be measured using the Profile of Mood States (POMS), which is one of the most widely used instruments in psychological research. POMS is not time sensitive, i.e. if a person’s mood is different today than it was yesterday, then the POMS will take that into account. A future line of research would be to use this method to design an experimental setup where one can measure the pre- and post-game mood of investors and examine its impact on the stock market by collecting their responses in a simulated investment decision game.

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TABLE 1: Summary Statistics of Returns on the First Trading Day After a One-day Match

Match	N	Mean	Std. dev.	Skewness	Kurtosis	K-S
NSE NIFTY INDEX						
Overall	2,735	0.029	1.557	-0.348	7.464	0.046***
No Matches	2,459	0.046	1.565	-0.389	7.803	0.046***
All Matches	276	-0.125	1.475	0.045	3.844	0.057
Winning Matches	143	-0.032	1.452	-0.034	3.887	0.079
Lost Matches	131	-0.231*	1.503	0.142	3.857	0.073
Matches Played in India	93	-0.139	1.429	-0.120	4.234	0.064
Matches Played Overseas	183	-0.118	1.501	0.115	3.667	0.058
Matches Won in India	53	-0.035	1.343	0.012	2.746	0.074
Matches Lost in India	40	-0.277	1.543	-0.173	5.206	0.133
Matches Won Overseas	90	-0.031	1.520	-0.053	4.217	0.084
Matches Lost Overseas	91	-0.210	1.494	0.293	3.173	0.076

Note: *, ** and *** indicate significant difference from 0 at 10%, 5% and 1% level respectively.

TABLE 2: Summary Statistics of Weekday Returns on the First Trading Day After a One-day Match: Breakdown According to Major Opponents

Opponent	All Matches			Wins			Losses		
	N	Mean	Std.	N	Mean	Std.	N	Mean	Std.
NSE NIFTY INDEX									
Australia	33	0.038	2.021	11	0.149	1.996	22	-0.018	2.078
England	16	0.005	1.389	9	0.460	1.640	7	-0.581*	0.729
New-Zealand	29	-0.167	0.852	14	0.226	0.908	15	-0.535**	0.621
Pakistan	44	-0.367	1.680	18	-0.526	1.501	26	-0.257	1.814
South Africa	31	-0.431	1.588	9	-0.328	1.845	22	-0.473	1.516
Sri-Lanka	45	0.127	1.439	23	0.229	1.485	21	0.062	1.439
West Indies	21	0.098	1.021	12	0.232	1.057	9	-0.082	1.002
Zimbabwe	33	-0.188	1.475	26	-0.340	1.568	6	0.232	0.936

Notes: *, ** and *** indicate significant difference from 0 at 10%, 5% and 1% level respectively.

TABLE 3: Results of the Dummy Variable Regression Model

	Win			Loss		
	N	Beta(W)	t-value	N	Beta(L)	t-value
NSE NIFTY INDEX						
All matches	143	0.078	0.63	131	-0.277**	-2.06
All matches with location dummy (India/Overseas)	143	0.067	0.45	131	-0.267*	-1.84
Matches in which Tendulkar played	118	0.069	0.49	100	-0.328**	-2.21
World Cup matches or final of some series	25	0.083	0.64	26	-0.282**	-2.07
Matches played against:						
Australia	11	0.121	0.21	22	-0.046	-0.11
England	9	0.431	0.83	7	-0.609**	-2.37
Kenya	11	0.161	0.70	2	-1.335***	-12.48
New Zealand	14	0.194	0.83	15	-0.565***	-3.58
Pakistan	18	0.561	1.63	26	-0.293	-0.84
South Africa	9	0.362	0.62	22	-0.506	-1.60
Sri Lanka	23	0.201	0.66	21	0.035	0.11
West Indies	12	0.203	0.69	9	-0.110	-0.35
Zimbabwe	26	0.372	1.23	6	-0.200	-0.57

Notes: *, ** and *** indicate significant at 10%, 5% and 1% level respectively.

TABLE 4: DD Test Results for the Effect of Cricket Matches on the Nifty Index.

	NSE NIFTY INDEX
DD Test Result	
1.	Cricket playing days >3 Non-cricket playing days
2.	Winning days >3 Non-cricket playing days
3.	Non-cricket playing days >2 Losing days
4.	Winning days >2 Losing days
5.	Tendulkar played >3 Non-cricket playing days
6.	Tendulkar played and won >3 Non-cricket playing days
7.	Non-cricket playing days >2 Tendulkar played and lost
8.	Tendulkar played and won >2 Tendulkar played and lost
9.	Won a match against Pakistan >3 Non-cricket playing days
10.	Non-cricket playing days >2 Lost a match against Pakistan
11.	Won a match against Pakistan >2 Lost a match against Pakistan
12.	Won a World Cup series /final of a series match >3 Non-cricket playing days
13.	Non-cricket playing days >3 Lost a World Cup Series / final of a series match
14.	Won a World Cup Series / final of a series match >2 Lost a World Cup / final of a series match

Notes: *X* >1 *Y* means *X* dominates *Y* at FSD, SSD and TSD; *X* >2 *Y* means that *X* dominates *Y* at SSD and TSD; *X* >3 *Y* means that *X* dominates *Y* at TSD at the 5% significance level.

FIGURE 1(a): CDF of Returns After Matches Lost and Normal Non-match Day Returns

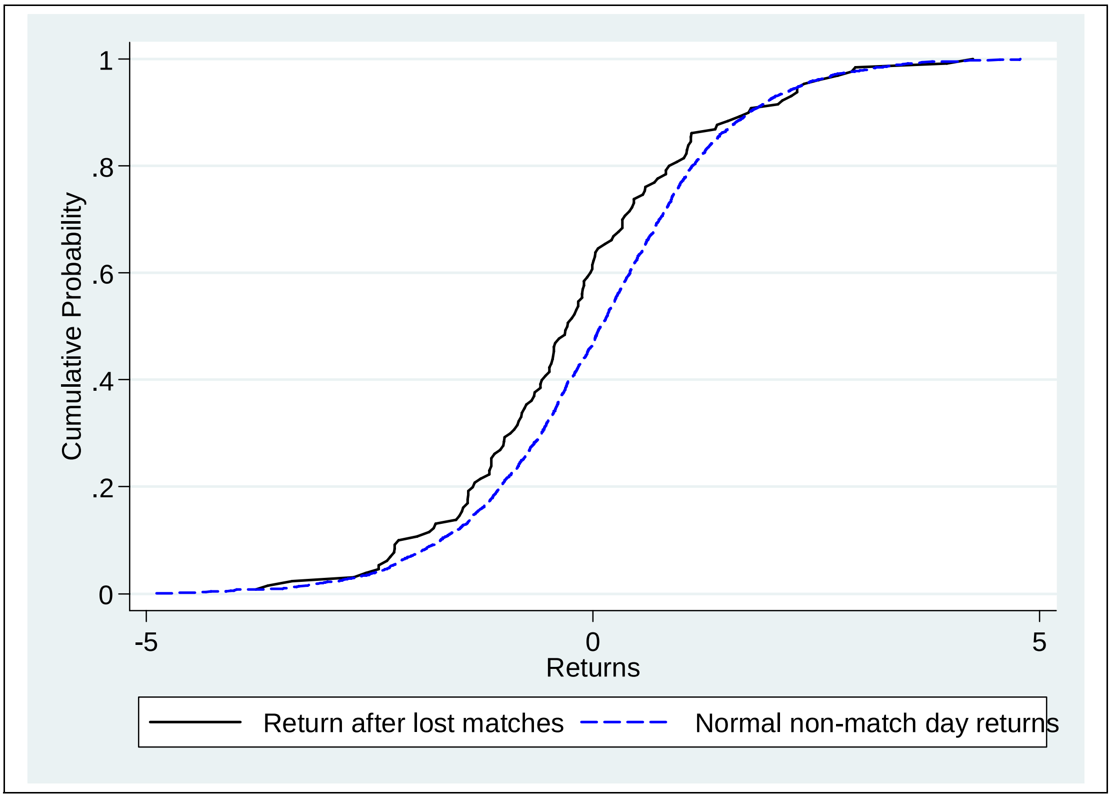


FIGURE 1(b): CDF of Returns After Matches Lost and Returns after Matches Won

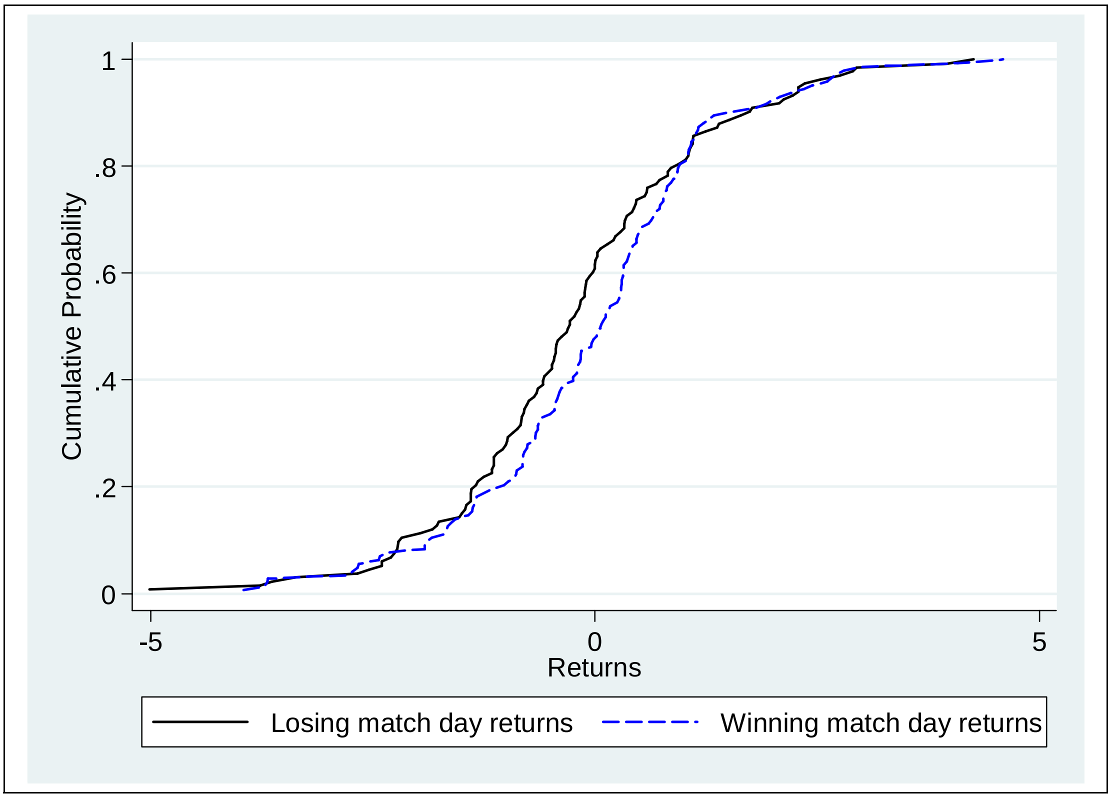


FIGURE 1(c): CDF of Returns After Matches in which Tendulkar Played

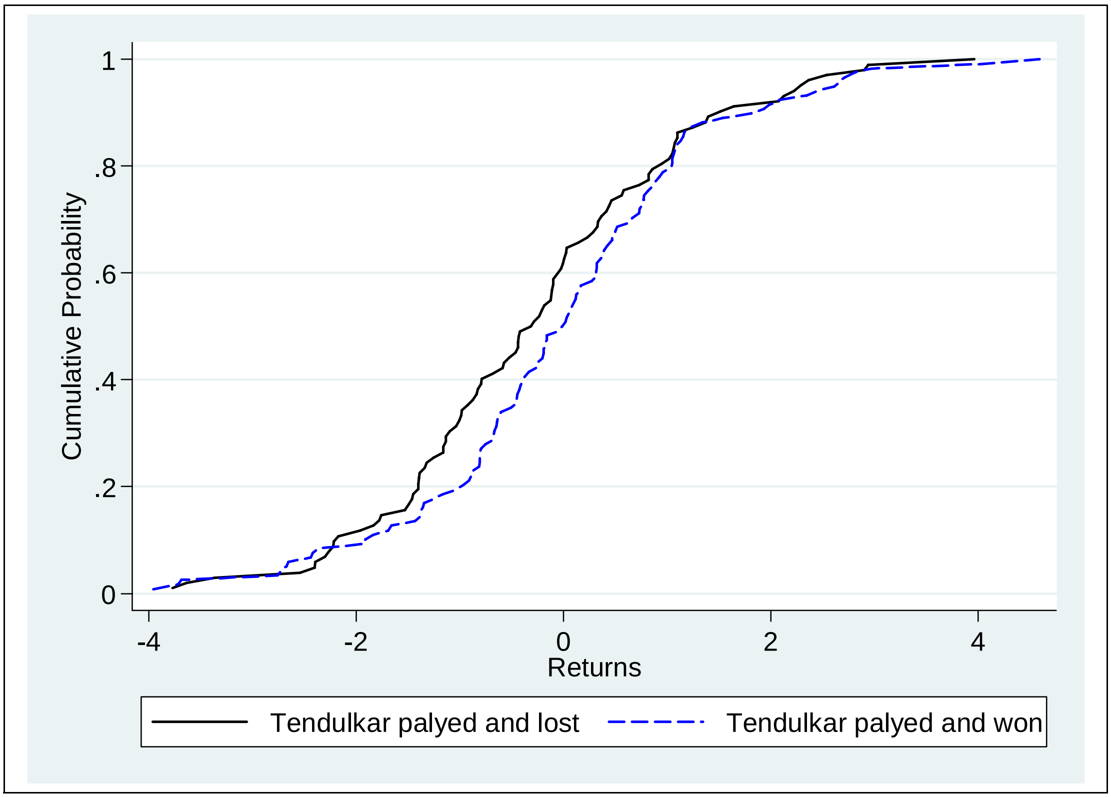


FIGURE 2(a): DD Statistics of Non-cricket Playing Days and Losing-Days Returns.

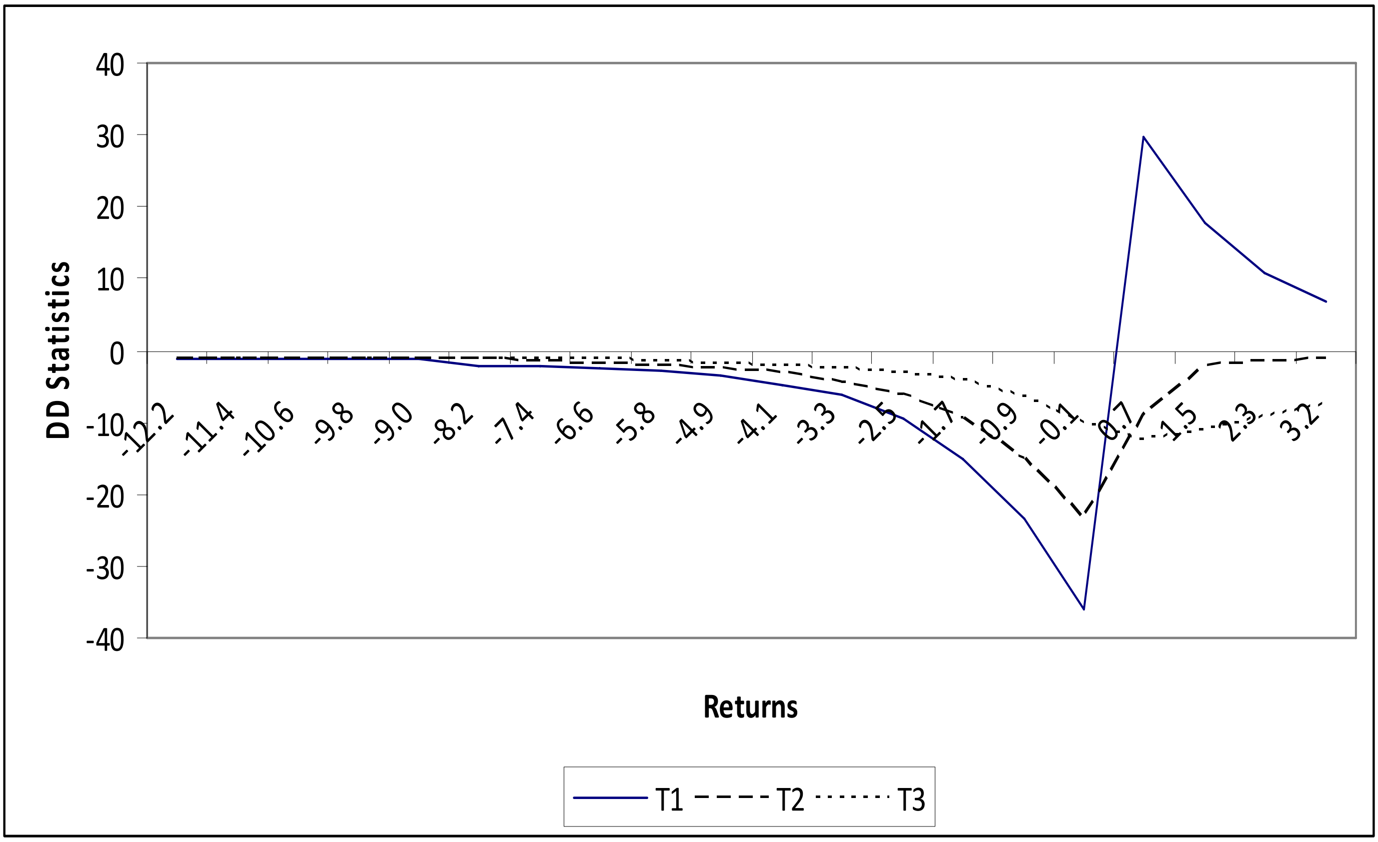


Figure 2(b): DD statistics of winning days returns and losing days returns.

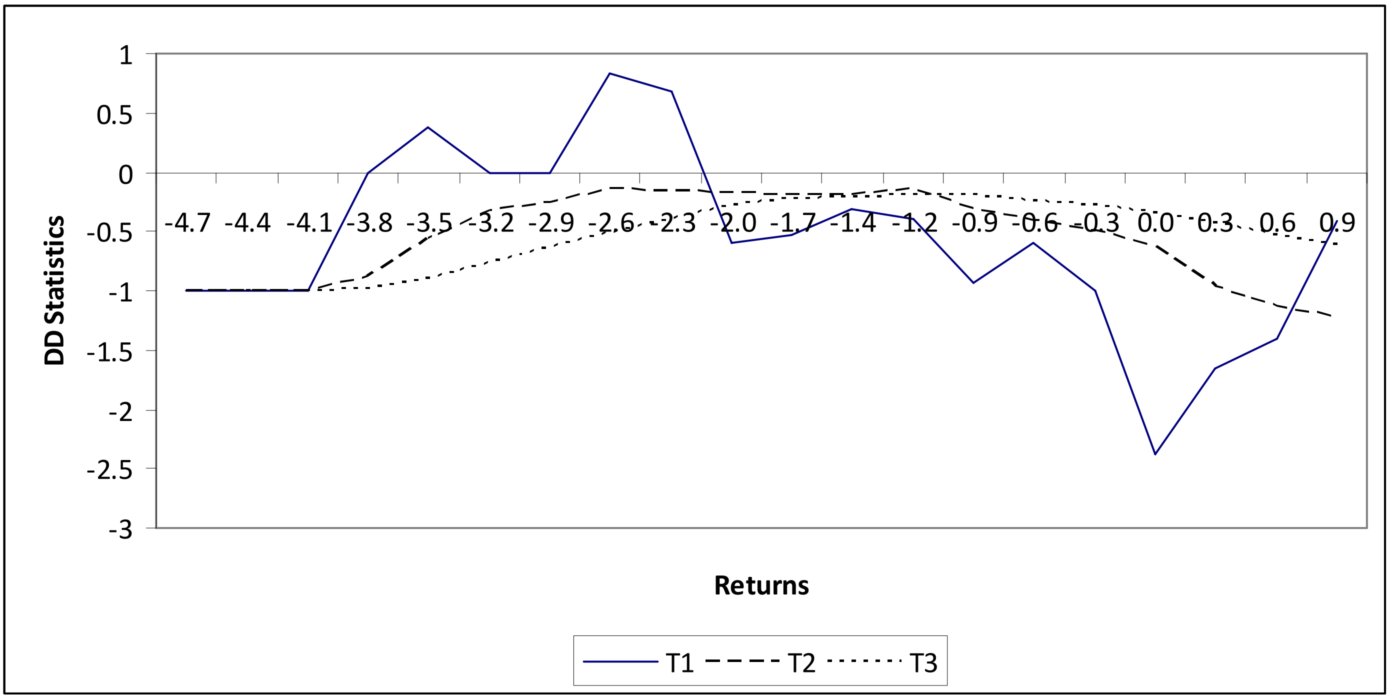


FIGURE 2(c): DD Statistics of Tendulkar Played and Lost Day Returns and Non-cricket Playing Days Returns

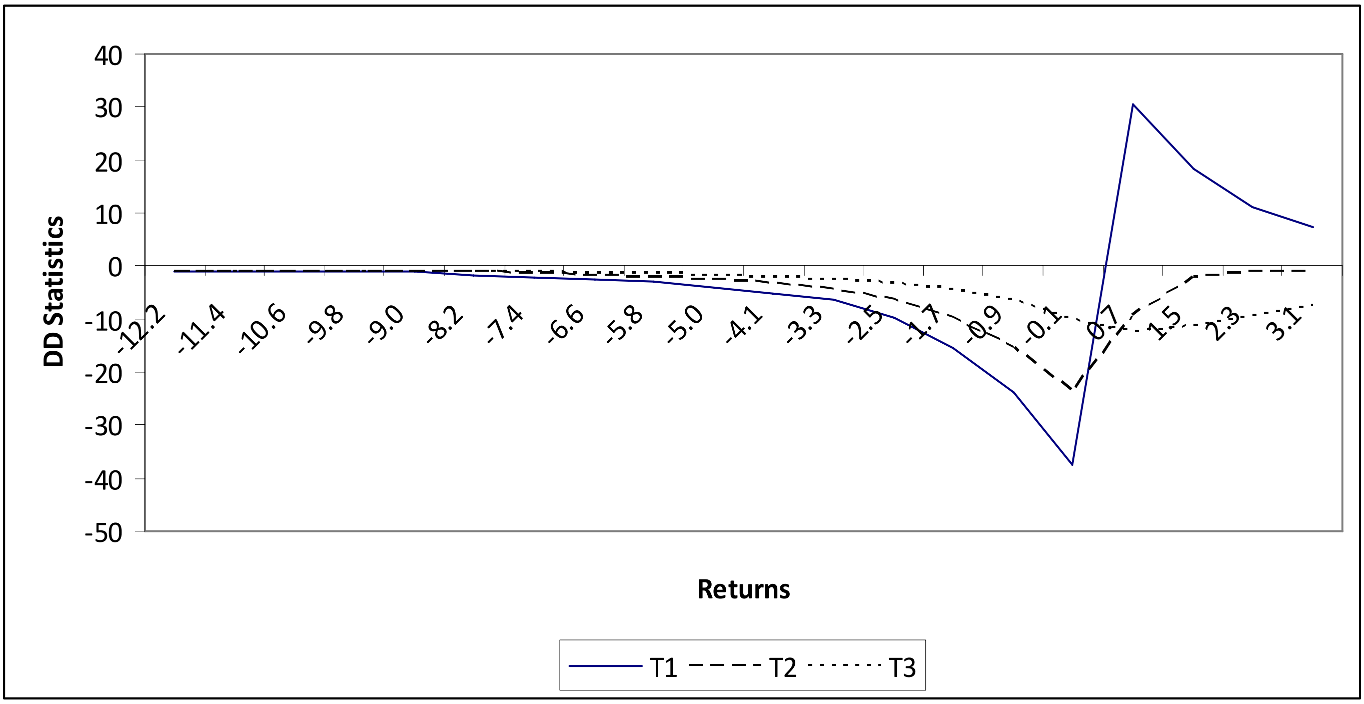
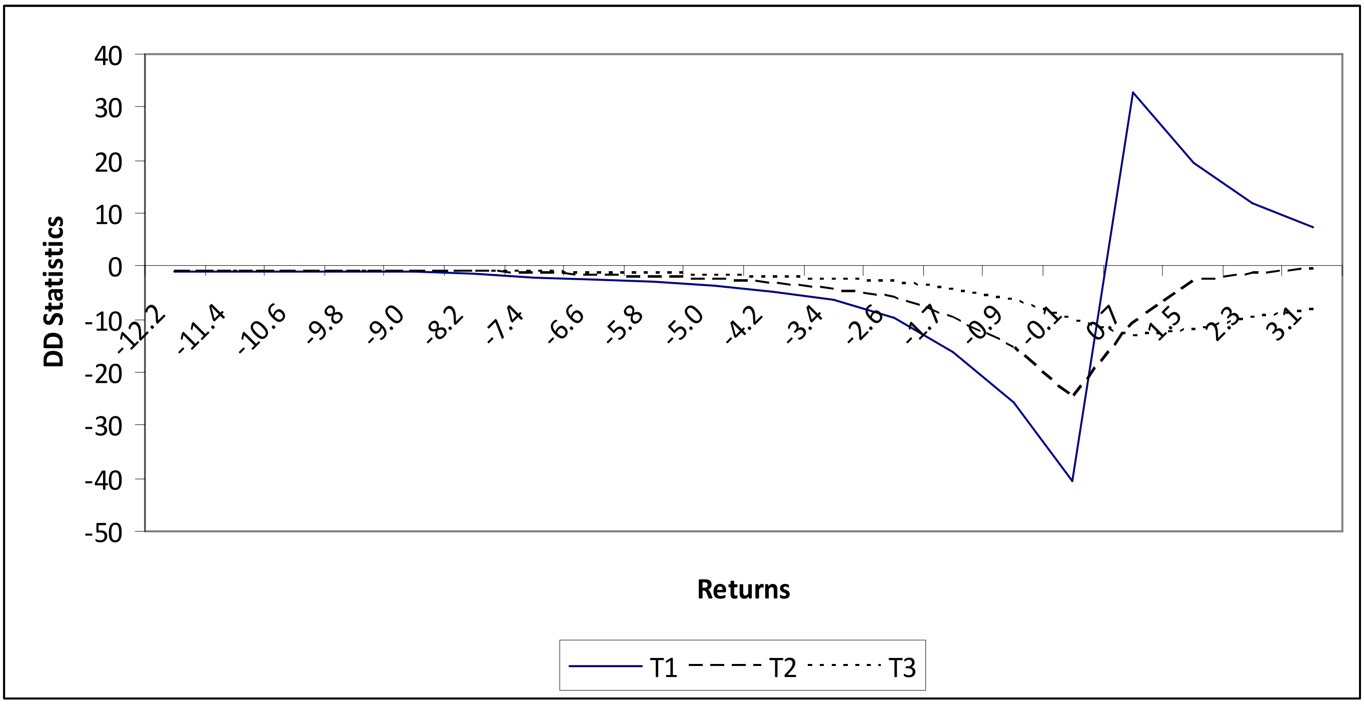


FIGURE 2(d): DD Statistics of Lost a Match Against Pakistan and Non-match Day Returns.



NOTES

[1] The non-satiation condition refers to the fact that more is preferred over less i.e. $(u'(x) > 0)$. Adding more wealth increases the agent's utility.

[2] Given the same mean for two distributions of returns, a risk averse investor will prefer the distribution with lower variance.