University of Pretoria
Department of Economics Working Paper Series

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Working Paper: 2018-71
November 2018

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Jumps Beyond the Realms of Cricket: India's Performance in One Day Internationals and Stock Market Movements

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Abstract

This study examines the impact of the Indian cricket team's performance in one day international (ODI) cricket matches on return, realized volatility and jumps of the Indian stock market, based on intraday data covering the period of 30th October, 2006 to 31st March, 2017. Standard linear Granger causality test fail to detect any evidence of wins or losses causing stock market movements. But given strong evidence of nonlinearity between our various stock market metrics and results of ODI matches, we next use a nonparametric causality-in-quantiles test, given the misspecification of the linear model. Using this data-driven robust approach, we were able to detect evidence of predictability from wins or losses for primarily volatility and jumps, especially over the lower-quantiles of the conditional distributions, with losses having stronger predictability than wins. However, the impact on stock return is weak and restricted towards the upper end of the conditional distribution. A closer look at our results tend to suggest that, when we control for misspecification, India's performances in ODI matches mainly affects large non-diversifiable risks (i.e., large jumps), and in the process drives market (systematic) risk (or uncertainty, which in turn has important implications for investors.

Keywords: Cricket, India, Stock market movements, Investor psychology

JEL Codes: C22, G1

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1. Introduction

"*Game's soul is not at Lord's. It is here*." -- Michael A. Atherton[1]

Following Baker and Wurgler (2006), there is an extensive literature on the impact of investors' and corporate managers' sentiments on movements in stock prices (see, Huang et al., (2015), Jiang et al., (forthcoming), and Zhou (forthcoming) for detailed discussions of this literature). Related to this line of research, several recent studies in behavioral finance tends to suggest that the sentiments of viewers cum investors are affected by the performance of the team they support in their favorite sports, which in turn, leads to upwards or downwards "mood swings" in the market and are reflected in stock prices.

This is an interesting finding, since a sporting event is a noneconomic phenomenon and hence, if the Efficient Market Hypothesis (EMH) does hold, one should not expect any impact on stock prices. However, the explanation for this observation can be drawn from neuroeconomics, whereby economists rely on the psychology literature which examines the impact of mood fluctuations on the decision making process. Formally speaking, the argument can be outlined as follows: the human brain has four lobes known as frontal, parietal, occipital and temporal. The frontal lobe performs the functions of planning, cognitive control and integration of cross-brain input, while the parietal lobe governs motor action. The occipital lobe is used for visual processing, and finally, 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. If all economic decisions were made by the frontal lobe of the brain, then all of them would conform to the rational utility maximization, however, because of the interaction between the frontal and temporal lobes, an economic decision will also depend on the emotional state of the individual. The upshot of this is that people in a good mood make optimistic judgments and choices, while the reverse happens in the state of a bad mood i.e., pessimistic judgments and choices.

Most of the existing papers on sporting events and stock price movements (see for example, Berument, et al (2006); Edmans et al. (2007); Kavetsos and Szymanski (2008); Klein et al. (2009); Scholtens and Peenstra (2009); Smith and Krige (2010); Kaplanski and Levy, (2010a, 2010b); Chen and Chen (2012); Pantzalis and Park (2014); Shu and Chang (2015); Curatola et al., (2016); Kaustia and Rantapuska (2016); Akhigbe et al., (2017); Dimic et al., (2018)) focus on the role of a multiple sporting event like the Olympics or soccer (football) matches, which is understandable, given the global reach of the sport. Comparatively, limited attention has been given to the role of cricket on stock market movements (barring a few notable exceptions like Edmans et al. (2007), Mishra and Smyth (2010), Abhijeet (2011), Abidin et al., (2011), Verstoep et al., (2015), Narayan et al., (2016)), which is a bit surprising, given that it is second most popular sport with more than 2.5 billion fans around the world.

In this regard, the paper by Edmans et al. (2007) was the first to identify significant downward trend in local stock markets of countries which suffered losses in cricket world cup matches. Inspired by this study, Mishra and Smyth (2010) examined the impact of the performance of the

[1] Michael A. Atherton is a broadcaster, journalist and a former England international first-class cricketer. And the above quote comes from one of his article on the importance of cricket in India, available at: https://www.thetimes.co.uk/article/games-soul-is-not-at-lords-it-is-here-7sq85l0rd.

Indian cricket team in One Day International (ODI) matches on stock returns. The paper showed that winning has no statistical significant upward movement while loss generates a significant downward movement in the stock market, with the effect being stronger when Sachin Tendulkar, India's most popular cricketer, plays and India loses. Abhijeet (2011) observed the reaction of two Indian stock indices (Sensex and Nifty) during the 2011 International Cricket Council (ICC) cricket world cup (held in India, Bangladesh and Sri Lanka) with respect to matches played by the Indian team. The author observed a positive upward trend in the markets when India won its matches, with the effect being even stronger when India won the final. However, Abidin et al. (2011) could not detect an impact of cricket match results on the stock markets of Australia and New Zealand. Verstoep et al., (2015) examined the influence of the investors' sentiment on the stock market following performances by the national cricket teams of India and Australia. They found no evidence of impact on spot or futures stock prices emanating from the performances of key players or the overall team, detected a 'mood effect' of poor performance by key players of national cricket teams in reduced trading volumes on the following day. Narayan et al., (2016) concentrated on the stock market reaction to investor mood swings resulting from the Indian Premier League (IPL) cricket matches, which in turn involves participation of international professional cricket players from all across the world representing various franchises owned by major corporate houses. They found that stocks listed on the Bombay Stock Exchange (BSE) that sponsor the IPL cricket are unaffected by the cricket matches. Overall, the results seem to be mixed on the impact of cricket match results on stock returns, but one observation that seems to stand out is that the impact on stock prices following wins or losses are likely to be asymmetric in nature.

Given this, the objective of the study is to examine the behavioral impact in national sentiment generated by the feeling of optimism or pessimism following a win or defeat respectively of the Indian cricket team involved in One Day International (ODI) matches on movements in the national stock market. The choice of India as our case study is unsurprising, because one-day cricket especially, is the number one spectator-sport in the country, and hence, has also been predominantly studied by the majority of the cricket-related papers mentioned above. Also as of last data available in 2011, cricket stood at a US$ 2.6 billion industry (Balasubramanian and Santhanam, 2011), which is sure to have grown exponentially in the last few years due to massive corporate investment into the sport as a result of India's strong performance. In addition, currently, as of 2017, India also has a sizeable number of people, to the order of 3.23 crores, investing in the stock market (BSE, 2017).

However, unlike the existing studies, given that investor sentiment has been shown to have effects on higher moments of stock markets (Balcilar et al., 2018a, b), we in this paper not only analyze the impact of India's performance in ODIs on stock return, but also on volatility. Note that financial market volatility is used as an important input in investment decisions, option pricing and financial market regulation (Poon and Granger, 2003). In light of this, financial market participants care not only about the nature of volatility, but also about its level, with all traders making the distinction between good and bad volatilities (Caporin et al., 2016). Good volatility is directional, persistent and relatively easy to predict, while, bad volatility is jumpy and comparatively difficult to foresee. Therefore, good volatility is generally associated with the continuous and persistent part, while bad volatility captures the discontinuous and jump component of volatility. Given this, it has been stressed that studying jumps can improve the overall understanding of the latent process of volatility (Gkillas et al., 2018; forthcoming). In light of this, we too in our study incorporate the impact of ODI match results involving India on the predictability of various types of volatility

jumps (small, big, good, and bad), besides return and realized volatility, as well as good and bad versions of the latter.

For our purpose, we use 5 minutes intraday data of the BSE (specifically the BSE200 index) covering the period of 30th October 2006 to 31st March 2017 to compute our daily return, realized volatility and volatility jumps, the predictability of which in turn, are analyzed based on information derived from India's ODI performances, i.e., both wins and losses, to check for possible asymmetry. As far as the econometric framework goes, we rely on the nonparametric causality-in-quantiles test of Jeong et al., (2012) for our predictability analysis, and hence, in the process capture various phases of the stock market variables. Understandably, the causality-in-quantiles test used here is inherently a time-varying approach as various parts of the conditional distribution of return, realized volatility and volatility jumps would relate to various points in time associated with the evolution of these variables. The causality-in-quantiles approach has the following two main novelties: First, it is robust to misspecification errors as it detects the underlying dependence structure between the examined time series. This is particularly important as we show that our stock market variables are nonlinearly associated with the dummy variable capturing wins or losses. And second, using this methodology, we are able to test not only for nonlinear causality-in-mean (1st moment), but also for causality over the entire conditional distribution of the stock market variables, including the tails. This is again of tremendous value since our dependent variables, i.e., return, realized volatility and volatility jumps are shown to be non-normal.

To the best of our knowledge, this is the first paper to analyze the predictability of any sporting event, and in particular cricket, for equity return, volatility and jumps, based on a causality-in-quantiles approach. Our results show evidence of predictability from wins or losses for primarily volatility and jumps, with the impact on stock return being weak. The remainder of the paper is organized as follows: Section 2 lays out the basics of the econometric methodologies involving realized volatility, volatility jumps and the causality-in-quantiles approach; Section 3 presents the data and results, with Section 4 concluding the paper.

2. Methodology

2.1. Intraday returns

Initially, we observe the price process in days t, consisting of $N+1$ intraday prices or N intraday returns, after removing one observation. Considering that the number of intraday returns per day is constant across all days, the returns during such intraday time periods cover $t_0 < t_1 < \cdots < t_{N+1}$. In our study, we excluded from our analysis the days with low variability resulting due to limited liquidity. However, there are few such intraday patterns in our sample, and are mainly during the early part. Generally, the index under consideration has satisfactory liquidity with a continuous trading history. Hence, the majority of intraday observations are employed in our dataset. Then, we calculate intraday returns as the logarithmic difference between two consecutively observed prices (5-minute by 5-minute), within a day, as:

$$r_{i,t} = \log(p_{i,t}) - \log(p_{i-1,t}) \quad (1)$$

where $r_{i,t}$ is intraday returns and $p_{i,t}$ accounts for the intraday price in 5-minutes i, $i = (1, \ldots, N)$, for the day t.

2.2. Realized variance and volatility jumps

We employ all available intraday returns to estimate daily realized volatility. For each day t, we retrieve a daily point estimate of the RV_t. The daily realized volatility is estimated as follows:

$$RV_t \equiv \sum_{i=1}^{N} r_{i,t}^2 \tag{2}$$

where RV_t is a benchmark realized volatility measure, $r_{i,t}$represents the 5-minute return i within a day t and $i = (1, \dots, N)$, where N is the total number of intraday observations within a day.

In the existing literature, there are several jump-robust realized volatility measures. For example, the study of Barndorff-Nielsen and Shephard (2006) was one of the first contributors in this regard who proposed the bi-power variation, with Mancini (2009) suggesting the threshold realized variance. Christensen et al. (2010) developed the quantile-based realized variance and Andersen et al., (2012)'s work deals with the "nearest neighbor truncation" estimators. However, in this paper, following, Bekaert and Hoerova (2014) we employ the threshold bipower variation $(TBPV_t)$ as a jump-free volatility estimator as defined in Corsi et al. (2010). Consequently, the $TBPV_t$ is defined as follows:

$$TBPV_t = \sum_{i=2}^{N} |r_{t,i-1}|, |r_{t,i}| I_{\{|r_{t,i-1}|^2 \le \theta_{i-1}\}} I_{\{|r_{t,i}|^2 \le \theta_i\}} \tag{3}$$

where $I_{\{\cdot\}}$ is the indicator function and the threshold function, $r_{t,i}$ is the 5-minute return series.

Then, we estimate the jump statistic $\left(ZJ_t^{(TBPV)} \right)$ following Duong and Swanson (2015), as follows:

$$ZJ_t^{(TBPV)} = \sqrt{N} \frac{(RV_t - TBPV_t) RV_t^{-1}}{[(\xi_1^{-4} + 2\xi_1^{-2} - 5) \max\{1, TQ_t TBPV_t^{-2}\}]^{1/2}} \tag{4}$$

where TQ_t stands for the realized tripower quarticity. The TQ_t is equal to $N\xi_{4/3}^{-3} \sum_{i=1}^{N} |r_{t,i}|^{4/3} |r_{t,i+1}|^{4/3} |r_{t,i+2}|^{4/3}$ and converges in probability to integrated quarticity. The $ZJ_t^{(TBPV)}$ follow a gaussian distribution. Hence, a jump is considered to be significantly different from zero if the $ZJ_t^{(TBPV)}$ exceeds the appropriate critical value of the standard Gaussian distribution, denoted by Φ_a, at a a significant level. Therefore, we estimate the significantly different from zero jump component of realized volatility, in a daily frequency, based on the following condition:

$$J_{t,a}^{(TBPV)} = |RV_t - TBPV_t| I_{\{ZJ_t^{(TBPV)} > \Phi_a\}} \tag{5}$$

where $I_{\{\cdot\}}$ is an indicator function of the $ZJ_t^{(TBPV)}$ exceeding of a given critical value. Finally, the continuous components $RVC_{t,a}$ is equal to $RV_t I_{\{ZJ_t^{(TBPV)} \le \Phi_a\}}$.

2.3. Realized semi-variance and upside and downside jumps

We estimate the downside (bad) and upside (good) semi-variance (realized volatility) in order to capture the sign asymmetry of the volatility process. These serve as measures of downside and upside risk, respectively. Following Barndorff-Nielsen et al., (2010), we estimate the realized semi-variances as follows:

$$RS_t^- = \sum_{i=1}^{N} r_{i,t}^2 \; I_{\{r_{i,t} < 0\}} \tag{6}$$

$$RS_t^+ = \sum_{i=1}^{N} r_{i,t}^2 \; I_{\{r_{i,t} > 0\}} \tag{7}$$

where $r_{i,t}$ represents the 5-minute return i within a day t and $i = (1, \dots, N)$, and N is the total number of intraday observations within a day.

Then, following the suggestion of Duong and Swanson (2011) and Duong and Swanson (2015), we estimate the downside and upside jumps. The downside and upside jumps are defined respectively, as follows:

$$RJ_t^- = I_{\left\{ZJ_t^{(TBPV)} > \Phi_a\right\}} \sum_{i=1}^{N} \left|r_{i,t}\right|^q I_{\{r_{i,t}<0\}} \tag{8}$$

$$RJ_t^+ = I_{\left\{ZJ_t^{(TBPV)} > \Phi_a\right\}} \sum_{i=1}^{N} \left|r_{i,t}\right|^q \; I_{\{r_{i,t}<0\}} \tag{9}$$

where the q is the asymmetry variable and affects the limiting behavior of the estimator. In this paper, we are interested in the case where $q \geq 2$, since large values of q, are dominated by large jumps. For $q < 2$, the jump variations are not always guaranteed to be finite. In our case, we selected q equal to 2.5. After that, we can very easily to estimate the corresponding asymmetric jump as in Duong and Swanson (2011) as follows:

$$RJA_t = I\left[ZJ_t^{(RV)} > \Phi_\alpha\right] \cdot \{RJ_t^+ - RJ_t^-\} \tag{10}$$

In all cases, we use the same jump detection schemes similar to the previous section. Therefore, downside, upside and asymmetric jumps are considered to be significant if the $ZJ_t^{(RV)}$ exceeds the appropriate critical value at a a significant level.

2.4. Small and large jumps

We estimate large and small jump variations as in the study of Duong and Swanson (2015) using decomposition based on a fixed truncation level (γ). Thus, the realized measure of truncated large jump variation, $RVLJ_t$, based on a jump detection schemes similar to the previous cases, is given by the following condition:

$$RVLJ_t = \min\left\{RVLJ_t, \left(\sum_{i=1}^{N} r_{i,t}^2 \cdot I_{|r_{i,t}|\geq\gamma}\right) \cdot \mathrm{I}[ZJ_t^{TBPV} > \Phi_\alpha]\right\} \tag{11}$$

Finally, the realized measure of truncated small jump variation is $RVSJ_t$, is given by the following condition:

$$RVSJ_t = RVJ_t - RVLJ_t \tag{12}$$

where represents RVJ_t the jump component.

2.5. Causality-in-Quantiles Test

This sub-section provides a brief description of the quantile based methodology based on the causality framework of Jeong et al., (2012). Let y_t denote either return, realized volatility, its good or bad versions, volatility jumps, and its various forms, i.e., good, bad, asymmetric, large and small jumps used in turn, and x_t denote the predictor variable, in our case the dummies capturing wins or losses, again considered separately.

Formally, let $Y_{t-1} \equiv (y_{t-1},...,y_{t-p})$, $X_{t-1} \equiv (x_{t-1},...,x_{t-p})$, $Z_t = (X_t, Y_t)$ and $F_{y_t|Z_{t-1}}(y_t, Z_{t-1})$ and $F_{y_t|Y_{t-1}}(y_t, Y_{t-1})$ denote the conditional distribution functions of y_t given Z_{t-1} and Y_{t-1}, respectively. If we denote $Q_\theta(Z_{t-1}) \equiv Q_\theta(y_t \mid Z_{t-1})$ and $Q_\theta(Y_{t-1}) \equiv Q_\theta(y_t \mid Y_{t-1})$, we have

$F_{y_t|Z_{t-1}}\{Q_\theta(Z_{t-1})\,|\,Z_{t-1}\}=\theta$ with probability one. Consequently, the (non)causality in the θ-th quantile hypotheses to be tested can be specified as:

$$H_0: \quad P\{F_{y_t|Z_{t-1}}\{Q_\theta(Y_{t-1})\,|\,Z_{t-1}\}=\theta\}=1, \tag{13}$$

$$H_1: \quad P\{F_{y_t|Z_{t-1}}\{Q_\theta(Y_{t-1})\,|\,Z_{t-1}\}=\theta\}<1. \tag{14}$$

Jeong et al., (2012) employ the distance measure $J=\{\varepsilon_t E(\varepsilon_t\,|\,Z_{t-1})f_z(Z_{t-1})\}$, where ε_t is the regression error term and $f_z(Z_{t-1})$ is the marginal density function of Z_{t-1}. The regression error ε_t emerges based on the null hypothesis in (1), which can only be true if and only if $E[1\{y_t \le Q_\theta(Y_{t-1})\,|\,Z_{t-1}\}]=\theta$ or, equivalently, $1\{y_t \le Q_\theta(Y_{t-1})\}=\theta+\varepsilon_t$, where $\mathbf{1}\{\cdot\}$ is an indicator function. Jeong et al. (2012) show that the feasible kernel-based sample analogue of J has the following form:

$$\hat{J}_T=\frac{1}{T(T-1)h^{2p}}\sum_{t=p+1}^{T}\sum_{s=p+1,s\neq t}^{T}K\left(\frac{Z_{t-1}-Z_{s-1}}{h}\right)\hat{\varepsilon}_t\hat{\varepsilon}_s. \tag{15}$$

where $K(\cdot)$ is the kernel function with bandwidth h, T is the sample size, p is the lag order, and $\hat{\varepsilon}_t$ is the estimate of the unknown regression error, which is estimated as follows:

$$\hat{\varepsilon}_t=1\{y_t \le Q_\theta(Y_{t-1})\}-\theta. \tag{16}$$

$\hat{Q}_\theta(Y_{t-1})$ is an estimate of the θth conditional quantile of y_t given Y_{t-1}, and we estimate $\hat{Q}_\theta(Y_{t-1})$ using the nonparametric kernel method as

$$\hat{Q}_\theta(Y_{t-1})=\hat{F}^{-1}_{y_t|Y_{t-1}}(\theta\,|\,Y_{t-1}), \tag{17}$$

where $\hat{F}_{y_t|Y_{t-1}}(y_t\,|\,Y_{t-1})$ is the *Nadarya-Watson* kernel estimator given by

$$\hat{F}_{y_t|Y_{t-1}}(y_t\,|\,Y_{t-1})=\frac{\sum_{s=p+1,s\neq t}^{T}L\left((Y_{t-1}-Y_{s-1})/h\right)1(y_s\le y_t)}{\sum_{s=p+1,s\neq t}^{T}L\left((Y_{t-1}-Y_{s-1})/h\right)}, \tag{18}$$

with $L(\cdot)$ denoting the kernel function and h the bandwidth.

The empirical implementation of causality testing via quantiles entails specifying three important choices: the bandwidth h, the lag order p, and the kernel type for $K(\cdot)$ and $L(\cdot)$ respectively. In this study, we use p=1 based on the Schwarz Information Criterion (SIC). The bandwidth value is chosen by employing the least squares cross-validation techniques. Finally, for $K(\cdot)$ and $L(\cdot)$ Gaussian-type kernels was employed.

3. Data and Results

Based on the availability of intraday data on the Indian stock market, specifically the Bombay Stock Exchange's (BSE) index called the BSE200, our analysis covers the period of 30th October 2006 to 31st March 2017, i.e., 2577 observations. This index is a free float weighted index of 200 companies based on specified and non-specified lists of the BSE, and is selected on the basis of their market capitalization. It started as a cap-weighted index with a base value of 100, and base year 1989-90. The data on stock index is derived from Datastream of Thomson Reuters. We also define two dummy variables corresponding to wins and losses in the One Day International matches played by the Indian cricket team. The dummy win (loss) is designed to take the value of

one (one) when India wins (loses) a match and zero otherwise, i.e., when they lose (win), there is no result following an abandonment, a tie, and also for stock market trading days when no matches are played. During the period of study, India played in 269 ODIs, won 159 of them, and lost 93, with 4 being tied and 13 having no results. The source of the data on cricket match information is: http://www.espncricinfo.com/. Table A1 summarizes the stock market related variables in the Appendix of the paper. As can be seen from the Jarque-Bera test of normality, all our stock market variables are non-normal – a results which provides preliminary motivation for using the quantiles-based method.

Now we are ready to analyze the results from our predictability exercise. Before we discuss the findings from the causality-in-quantiles test, for the sake of completeness and comparability, we first conducted the standard linear Granger causality test, with a lag-length of 1, as determined by the SIC. The resulting $\chi^2(1)$ statistics obtained from the linear model applied on our various stock market metrics involving returns, realized volatility and jumps have been reported in Table 1. As can be observed, there is no evidence of predictability in any of the cases (including returns as observed by some earlier studies), even at the 10 percent level of significance.

Given this evidence of lack of predictability, and realizing the possibility that financial market variables are likely to be nonlinearly related with its predictors, we next statistically examine the presence of nonlinearity in the relationship between our stock market variables and the win and loss dummies separately. Nonlinearity, if present, would motivate the use of the nonparametric quantiles-in-causality approach, as the quantiles-based test would formally address nonlinearity in the relationship between the two variables under investigation. For this purpose, we apply the Brock et al., (1996, BDS) test on the residuals from the equations involving our various stock market metrics with one lag of the particular stock market variable under consideration and the win or loss dummy. Table 2 presents the results of the BDS test of nonlinearity. As shown in this table, we find strong evidence, at highest level of significance, for the rejection of the null of *i.i.d.* residuals at various embedded dimensions (m), which in turn, is indicative of nonlinearity in the relationship between our stock market variables and India's wins or losses. This finding of nonlinearity indicate that, the result of no-predictability based on the linear Granger causality tests, cannot be deemed robust and reliable.

Given the strong evidence of nonlinearity in the relationship between our stock market variables and India's performance in ODI matches, we now turn our attention to the causality-in-quantiles test, which is robust to misspecification due to its nonparametric (i.e., data-driven) approach. As can be seen from Table 3, which reports this test for the quantile range of 0.05 to 0.95, the null that win or loss does not Granger cause our stock market variables are quite similar in terms of the quantiles for which the null is rejected, but predictability is stronger under the loss dummy than under win. We can say this, since we normalized these dummies to have a standard deviation of one and hence, the strength of predictability is comparable. The above result tends to suggest that the optimism introduced by a win, is not as big in magnitude as pessimism following a loss. In general, predictability of return is the weakest, with the impact restricted to upper conditional quantiles, i.e., 0.80-0.90. For the other stock market variables predictability in general covers the lowest quantile (0.05) to above the median with the exceptions of the extremely high quantiles or the highest quantile, with the exception of the large jumps, i.e., *RVLJ*. Another exception is the variable capturing the asymmetry in the jumps, i.e., *RVLJ*, for which predictability is centered around the

median over the quantile range of 0.25 to 0.80, and thus, excludes the extreme ends of the conditional distribution. In sum, India's ODI match performance seems to drive volatility more than return, with stronger effects observed under losses than wins, and also towards the lower end of the conditional distribution. In addition, the movements in volatility is primarily driven by the impact of wins or losses on volatility jumps (particularly large one, i.e., *RVLJ*) – a result that motivates the decision to look beyond return and into volatility, and also the role of jumps in governing the latent process of volatility. Hence, the impact of ODI match results is observed to affect more the risk profile of the Indian stock market rather than the return, which in turn, could explain the conflicting results of the earlier studies dealing only with stock market return movements, and not looking at higher moment effects.[2]

4. Conclusion

The objective of the study is to examine the behavioral impact in national sentiment generated by the feeling of optimism or pessimism following a win or defeat respectively of the Indian cricket team involved in ODI matches on movements in the national stock market. While analyzing the stock market impacts, we go beyond the existing literature in not only concentrating on return, but also volatility and volatility jumps. For our purpose, we use 5 minutes intraday data of the BSE200 index covering the period of 30th October 2006 to 31st March 2017 to compute our daily return, realized volatility and volatility jumps, the predictability of which in turn, are analyzed based on information derived from India's ODI performances, i.e., both wins and losses. In terms of the econometric framework goes, we rely on the nonparametric causality-in-quantiles test of Jeong et al., (2012) for our predictability analysis, which in turn, is robust to misspecification due to nonlinearity, being a data-driven procedure.

Starting off with the standard linear causality test, we were unable to detect any evidence of India's ODI match performances causing return, volatility or jumps. But, we indicate that linear Granger causality test results cannot be relied upon because formal tests reveal strong evidence of nonlinearity between the stock market variables and the measure of investor mood, i.e., wins or losses. Hence, linear Granger causality tests are misspecified. When we use the nonparametric causality-in-quantiles test instead, we were able to detect evidence rejecting the null hypothesis that wins or losses does not Granger cause volatility and jumps, especially over the lower-quantiles of the conditional distributions, with losses having stronger predictability than wins. The impact on stock return is however, weak and restricted towards the upper end of the conditional distribution. Thus, our results indicated that when we control for misspecification due to nonlinearity, it is

[2] To check for the robustness of our results, and also for the sake of comparability, we also conducted the same analyses for Pakistan, another nation, just like India, where cricket is the most important spectator-sport. The same sample period of 30th October, 2006 to 31st March 2017 is considered, giving us a total of 2581 trading days for the Karachi Stock Exchange (KSE), where we look at specifically the movements in KSE100 index. During this period, Pakistan played in 217 ODIs, won 109 of them, and lost 102, with 2 being tied and 4 having no results. The sources for the stock market and the cricket related data are the same as that for India. The results have been reported in Table A2 of the Appendix. While results are in general similar to those of India, in the sense that volatility movements are primarily driven by jumps, the stark difference that is observed comes from the stock market return. In case of Pakistan, results of ODI matches do tend to predict the entire conditional distribution of the return. So unlike India, for Pakistan, the impact is stronger on return, than on the risk profile, in terms of the coverage of predictability over the respective conditional distributions. This could be because of the relatively stronger influence of large jumps in the BSE200 driving the volatility process than compared to the KSE100 where the win or losses does not impact bad volatility (RS^-), i.e., in case of India, results of matches have sudden large changes than consistent impact throughout the trading hour.

indeed true that wins or losses of the Indian cricket team in ODI matches can predict movements in volatility and volatility jumps. In sum, recalling the importance of jumps in the volatility process, our results tend to suggest that the channel through which results of ODI matches affect low to moderately high (conditional) volatility, is primarily through (large) jumps. This result has important implications for decisions of investors, in the sense that results of ODI matches, in particular losses, would tend to impact the risk profile of the Indian equity market, with the predictability emanating from primarily large non-diversifiable risks (i.e., large jumps). In other words, cricket match results of the Indian team can be utilized to predict market or systematic risk, i.e., uncertainty, and would allow for accurate pricing of securities by proving ahead of time information on the risk-premium. Understandably, if investors are aiming control for such systematic risks, they need to devise appropriate hedging strategies.

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Table 1: Linear Granger causality

Dependent variable	Independent variable	$\chi^2(1)$-statistic	p-value
r_i	Win	0.0126	0.9105
	Loss	1.3391	0.2473
RV	Win	0.0041	0.9492
	Loss	0.0012	0.9723
RJ	Win	0.0038	0.9507
	Loss	0.2147	0.6431
RS^-	Win	0.7281	0.3936
	Loss	0.0525	0.8188
RS^+	Win	0.0661	0.7971
	Loss	1.1233	0.2893
RJ^-	Win	0.0236	0.8778
	Loss	0.0645	0.7996
RJ^+	Win	0.0025	0.9601
	Loss	0.0013	0.9713
RJA	Win	0.0279	0.8673
	Loss	0.0818	0.7749
$RVLJ$	Win	0.0478	0.8269
	Loss	0.1081	0.7423
$RVSJ$	Win	0.4455	0.5045
	Loss	0.0054	0.9413

Note: The null hypothesis is that Win or Loss does not Granger cause the stock market variables, where, r_i, RV, RJ, RS^-, RS^+, RJ^-, RJ^+, RJA, $RVLJ$, $RVSJ$ stands for return, realized volatility, volatility jump, bad volatility, good volatility, bad jumps, good jumps, asymmetric jumps, large jumps and small jumps respectively.

Table 2: BDS Test of Nonlinearity

Dependent variable	Independent variable	Dimension				
		2	3	4	5	6
r_i	Win	11.558***	15.718***	18.714***	21.477***	23.856***
	Loss	11.546***	15.715***	18.703***	21.460***	23.840***
RV	Win	24.832***	29.719***	33.348***	36.779***	40.548***
	Loss	24.825***	29.713***	33.342***	36.772***	40.537***
RJ	Win	4.796***	5.823***	6.925***	7.580***	7.721***
	Loss	4.654***	5.660***	6.710***	7.344***	7.611***
RS^-	Win	26.764***	31.654***	34.903***	38.370***	42.220***
	Loss	27.190***	31.830***	34.951***	38.240***	41.986***
RS^+	Win	28.958***	33.328***	36.954***	40.705***	45.237***
	Loss	28.803***	33.142***	36.855***	40.620***	45.129***
RJ^-	Win	8.009***	9.821***	11.217***	12.574***	13.787***
	Loss	8.640***	9.963***	11.537***	12.913***	14.209***
RJ^+	Win	8.092***	9.504***	10.967***	12.554***	14.064***
	Loss	8.290***	9.636***	11.085***	12.642***	14.099***
RJA	Win	1.825*	4.732***	6.884***	8.344***	9.049***
	Loss	1.707*	4.312***	6.423***	7.881***	8.578***
RVLJ	Win	10.782***	12.739***	14.553***	16.458***	18.411***
	Loss	10.739***	12.682***	14.493***	16.392***	18.352***
RVSJ	Win	11.014***	12.593***	13.710***	14.955***	16.425***
	Loss	11.049***	12.647***	13.780***	15.032***	16.516***

Note: See Notes to Table 1. Entries correspond to the *z*-statistic of the BDS test with the null of *i.i.d.* residuals, with the test applied to the residuals recovered from the equation involving the various stock market variables with one lags each of the stock market variable under consideration and Win or Loss; *** (*) indicates rejection of the null hypothesis at 1 (10) percent level of significance.

Table 3. Causality-in-Quantiles Results for the Stock Market of India

Dependent variable	Independent variable	Quantile										
		0.05	0.10	0.20	0.30	0.40	0.50	0.60	0.70	0.80	0.90	0.95
r_i	Win	0.69	0.92	0.60	0.50	0.83	1.83*	1.24	1.57	2.13**	2.70***	1.90*
	Loss	0.71	0.90	0.75	0.68	0.88	1.64	1.13	1.38	2.20**	2.70***	2.04**
RV	Win	2.96***	6.93***	4.50***	3.27***	2.63***	2.57***	1.60	1.11	0.71	0.45	0.48
	Loss	2.84***	6.77***	4.99***	3.56***	2.70***	2.50**	1.68*	1.18	0.79	0.53	0.57
RJ	Win	1619.95***	955.88***	446.35***	211.54***	82.37***	16.62***	0.43	0.52	0.41	0.27	0.31
	Loss	1699.12***	1004.61***	472.21***	226.42***	90.33***	19.70***	0.60	0.62	0.43	0.33	0.39
RS^-	Win	3.71***	9.70***	16.34***	20.77***	24.17***	26.18***	18.28***	8.78***	4.43***	0.22	0.15
	Loss	3.15***	9.63***	17.26***	21.38***	25.34***	26.78***	18.45***	8.71***	4.98***	0.43	0.35
RS^+	Win	4.51***	13.70***	22.43***	19.99***	13.89***	7.20***	6.95***	4.61***	2.08**	1.56	1.31
	Loss	4.84***	14.22***	22.96***	21.22***	14.85***	8.16***	7.50***	4.82***	2.28**	1.86*	1.45
RJ^-	Win	2191.00***	1304.54***	612.04***	289.16***	111.07***	21.04***	0.02	0.02	0.03	0.04	0.01
	Loss	2292.88***	1368.07***	645.57***	308.03***	120.81***	24.59***	0.04	0.05	0.07	0.05	0.06
RJ^+	Win	1943.44***	1147.28***	533.74***	250.77***	95.73***	17.88***	0.23	1.09	0.93	0.79	0.36
	Loss	2031.82***	1201.89***	562.25***	266.67***	103.84***	20.82***	0.39	1.33	1.02	0.89	0.35
RJA	Win	0.00	0.00	0.00	1087.67***	665.66***	380.40***	185.17***	60.32***	2.45**	0.00	0.00
	Loss	0.00	0.00	0.00	1087.91***	665.85***	380.54***	185.27***	60.37***	2.47**	0.00	0.00
RVLJ	Win	1446.13***	858.74***	406.19***	196.05***	79.12***	17.95***	0.86	1.92*	6.55***	4.87***	1.70*
	Loss	1509.14***	897.67***	426.88***	207.96***	85.52***	20.56***	1.23	1.70*	6.55***	4.75***	1.84*
RVSJ	Win	2323.11***	1389.25***	664.92***	326.26***	135.79***	33.45***	0.05	0.05	0.07	0.07	0.03
	Loss	2419.66***	1451.22***	698.39***	345.52***	146.13***	37.73***	0.16	0.08	0.11	0.13	0.08

Note: See Notes to Table 1; DV (IV) stands for dependent variable (independent variable); The entries correspond to the standard normal statistic testing whether Win or Loss Granger causes the various stock market variables at a specific quantile. ***,**, * indicates rejection of the null hypothesis of no-causality at 1, 5 and 10% levels of significance respectively., with corresponding critical values of 2.575, 1.96 and 1.645.

APPENDIX:

Table A1. Summary Statistics

	Variables									
Statistic	r_i	*RV*	*RJ*	RS^-	RS^+	RJ^-	RJ^+	*RJA*	*RVLJ*	*RVSJ*
Mean	0.0307	1.1099	0.0443	0.9187	0.7918	0.0394	0.0156	-0.0238	0.2264	0.2092
Median	0.1007	0.5610	0.0000	0.3231	0.3068	0.0000	0.0000	0.0000	0.0000	0.0000
Maximum	6.9096	79.1496	12.3791	144.3269	40.8237	41.6626	6.5821	1.0079	40.7482	26.0223
Minimum	-11.3453	0.0088	0.0000	0.0027	0.0049	0.0000	0.0000	-35.0805	0.0000	0.0000
Std. Dev.	1.4324	2.4435	0.2793	3.9368	2.0188	0.9095	0.1403	0.7886	0.9768	0.7272
Skewness	-0.6037	16.5951	34.5407	24.0290	9.2649	41.1151	40.5116	-39.5799	28.9953	19.3844
Kurtosis	8.6688	449.7622	1484.8450	765.6202	123.9778	1787.8280	1868.1110	1648.8260	1157.9790	628.3937
Jarque-Bera	3605.656	21541587	2.36E+08	62671844	1607746	3.43E+08	3.74E+08	2.91E+08	1.44E+08	42141245
p-value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Observations	2576									

Note: See Notes to Table 1. Std. Dev. stands for standard deviation, while probability is the *p*-value for the Jarque-Bera test, with the null hypothesis of normality.

Table A2. Causality-in-Quantiles Results for the Stock Market of Pakistan

Dependent variable	Independent variable	Quantile										
		0.05	0.10	0.20	0.30	0.40	0.50	0.60	0.70	0.80	0.90	0.95
r_i	Win	1.81*	4.78***	4.83***	4.25***	2.53**	2.35**	2.41**	1.95*	3.01***	3.14***	1.69*
	Loss	1.68*	4.35***	4.99***	4.94***	2.99***	2.58***	2.87***	2.11**	2.89***	3.22***	1.83*
RV	Win	0.15	0.47	1.32	2.19**	3.20***	2.87***	1.95*	1.19	0.56	0.19	0.05
	Loss	0.16	0.42	1.25	2.24**	3.15***	2.91***	2.05**	1.44	0.65	0.17	0.05
RJ	Win	1454.29***	872.11***	418.51***	205.73***	85.84***	21.36***	0.28	0.27	0.27	0.37	0.28
	Loss	1501.72***	902.38***	435.41***	215.97***	91.72***	24.00***	0.36	0.25	0.25	0.27	0.22
RS^-	Win	0.01	0.03	0.08	0.09	0.15	0.21	0.24	0.25	0.27	0.19	0.09
	Loss	0.01	0.04	0.10	0.15	0.20	0.29	0.31	0.34	0.25	0.16	0.09
RS^+	Win	0.07	0.24	0.72	1.35	1.66*	2.12**	1.89*	1.16	0.62	0.20	0.07
	Loss	0.08	0.24	0.67	1.13	1.59	2.13**	1.78*	1.09	0.66	0.23	0.10
RJ^-	Win	1988.49***	1181.63***	561.74***	274.29***	113.48***	27.56***	0.08	0.23	0.25	0.25	0.24
	Loss	2045.71***	1218.59***	583.15***	287.88***	121.72***	31.53***	0.20	0.20	0.34	0.33	0.22
RJ^+	Win	1456.53***	874.35***	420.18***	206.89***	86.59***	21.75***	0.32	1.50	1.81*	1.93*	1.67*
	Loss	1503.71***	904.48***	437.02***	217.11***	92.48***	24.41***	0.41	1.17	1.41	1.75*	1.46
RJA	Win	0.02	0.02	0.01	1063.87***	651.86***	373.52***	182.85***	60.48***	2.84***	0.01	0.02
	Loss	0.02	0.02	0.07	1066.89***	654.24***	375.33***	184.15***	61.24***	3.00***	0.01	0.04
RVLJ	Win	2257.65***	1346.57***	641.34***	312.76***	128.76***	30.74***	0.09	0.05	0.15	0.20	0.15
	Loss	2313.89***	1383.20***	662.84***	326.58***	137.23***	34.83***	0.12	0.21	0.39	0.26	0.17
RVSJ	Win	1882.88***	1118.69***	534.67***	264.15***	112.04***	29.36***	0.34	0.39	1.60	0.97	0.50
	Loss	1943.05***	1157.55***	557.20***	278.48***	120.80***	33.69***	0.73	0.35	1.25	0.82	0.49

Note: See Notes to Table 1 and Table 3.