TOO BUSY FOR RISK? MEASURING THE DISTRACTION EFFECT OF MARCH MADNESS ON FINANCIAL

By

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Content

Abstract

This paper investigates whether investor distraction during NCAA March Madness leads to increased Value at Risk (VaR) model violations. Using stock return data from 2023 to 2025, we compare companies linked to the tournament with control firms. Contrary to expectations, we find that treatment firms experienced fewer VaR breaches during game days. These results suggest that attention-based effects may vary depending on firm characteristics, and that media involvement might attract additional market scrutiny rather than reduce it.

1 Introduction

Every March, millions of Americans immerse themselves in the NCAA Men's Basketball Tournament, an event so culturally significant that it is known simply as "March Madness." In 2025, I found myself deeply drawn into the tournament, watching games, tracking brackets, and following dramatic upsets. This personal experience led me to wonder: if I, someone studying risk management, could become so distracted, what about institutional investors? Could this widespread attention shift cause real distortions in the way financial risks are monitored?

This paper investigates whether investor distraction during March Madness impacts the accuracy of Value at Risk (VaR) models. VaR is a commonly used risk forecasting tool, but its reliability depends on investor responsiveness to market signals. When attention is diverted, especially during high-stakes sports events, market reactions may slow down or become more volatile. This could cause VaR models to underestimate real losses.

To explore this hypothesis, I examine a set of companies closely associated with March Madness, including betting platforms, sponsors, and media broadcasters. I compare them to firms with no involvement in the tournament. By analyzing their VaR violation patterns on game days and non-game days, this study aims to shed light on the intersection between investor behavior, media-driven distraction, and risk model performance.

2 Literature Review

2.1 Behavioral Biases and Attention in Financial Markets

A growing body of literature has emphasized how investor sentiment and cognitive attention can influence financial market outcomes. Hirshleifer and Shumway (2003) demonstrated that seemingly unrelated variables such as weather and mood could predict market returns. Edmans et al. (2007) further found that international soccer losses, which trigger negative emotions among fans, can lead to significant short-term declines in national stock indices. These studies provide evidence that non-fundamental, psychological factors can temporarily distort investor decision-making and affect market behavior.

2.2 Sports Events and Market Distraction

March Madness, the annual NCAA basketball tournament, is one of the most widely viewed sporting events in the United States. It has been shown to command high levels of public attention, which may spill over into the financial domain. Kaplanski (2010) was among the first to investigate whether such large-scale sporting events distract investors and increase market volatility. The study found significant increases in risk measures during the tournament period. More recent work, such as Kim (2023), applies machine learning approaches to March Madness prediction, but focuses primarily on forecasting sports outcomes rather than financial implications.

In another related study, Abuzayed et al. (2013) examined whether sports sentiment affects firm-specific performance and investor decisions, showing a significant connection between institutional mood and earnings announcement anomalies. These findings collectively support the hypothesis that high-attention periods like March Madness may impair investor vigilance, leading to systematic deviations in risk outcomes.

2.3 Risk Measurement and Causal Inference

Value-at-Risk (VaR) is a widely used metric in both academia and industry to quantify the downside risk of financial assets. A VaR violation occurs when actual returns fall below the predicted threshold, signaling an underestimation of risk. In this study, VaR violations are used as a practical measure of whether market participants were effectively managing risk expectations during periods of potential distraction.

To identify the causal effect of Game Day exposure on subsequent risk violations, we employ a quasi-experimental framework that integrates propensity score estimation and Augmented Inverse Probability Weighting (AIPW). These methods, rooted in the potential outcomes framework (Rubin, 1974; Imbens and Rubin, 2015), help mitigate selection bias and estimate the Average Treatment Effect (ATE) under observable confounders.

2.4 Sports Mood and Investor Distraction Effects

Wu (2022) constructed a Sports Mood Index (SMI) based on the performance of professional sports teams in 49 metropolitan areas across the United States and Canada. By tracking institutional investor holdings, the study used SMI as a proxy for investor sentiment. The findings suggest that during periods of negative sports-induced mood, institutional investors became more conservative, which led to higher earnings announcement premiums and weaker post-earnings announcement drift (PEAD). These results illustrate how investor mood can influence the interpretation and pricing of financial information.

While Wu's focus was on asset pricing anomalies following earnings announcements, I extend this framework by shifting attention to the quality of risk management. Specifically, I examine whether emotionally distracting events, such as NCAA March Madness game days, are associated with increased occurrences of Value-at-Risk (VaR) violations. This perspective allows me to explore whether distraction impairs the execution of risk control procedures rather than merely affecting price reaction.

To highlight the conceptual differences between Wu's study and mine, I include a side-by-side flowchart (see Figure X in the Methodology section). The chart compares the two studies across five components: input variables, treatment indicator, outcomes, methodology, and conclusion. In my design, March Madness game days serve as a binary treatment, and I apply a combination of propensity score estimation and Augmented Inverse Probability Weighting (AIPW) to estimate the average treatment effect (ATE) on risk management failure.

3 A Methodology

3.1 Research Design Overview

To investigate whether March Madness game days distract investors and lead to a breakdown in risk control, I conduct an event-based observational study. I treat each NCAA March Madness game day as a binary treatment indicator and compare its effect on subsequent Value-at-Risk (VaR) violations using both summary statistics and causal inference methods. A detailed comparison between this study and Wu (2022) is presented in Figure 3.1, which outlines the parallel research components and illustrates how this research builds upon and diverges from prior literature.

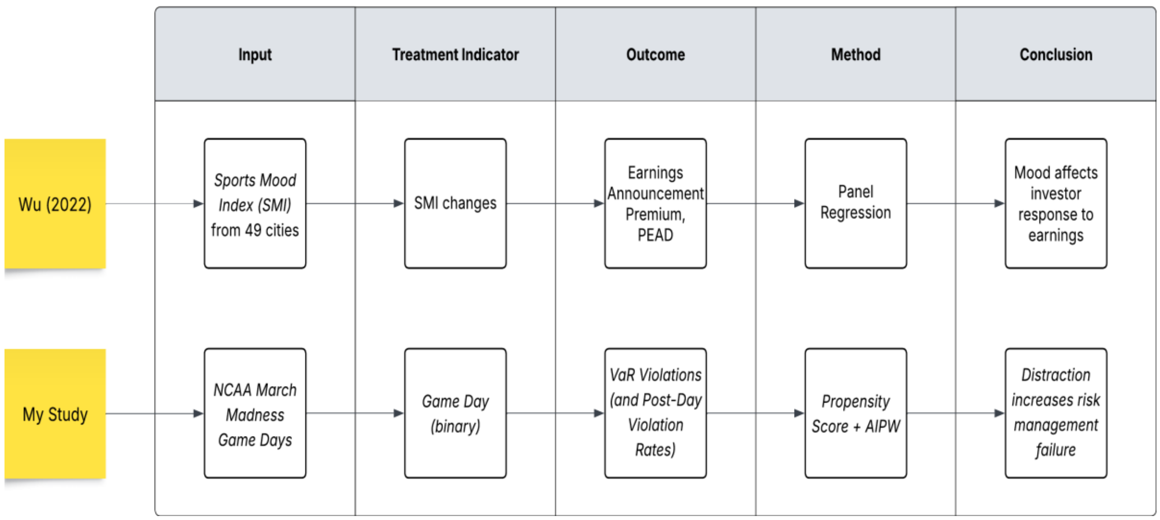

Figure 3.1. Conceptual Framework Comparison between Wu (2022) and My Study

3.2 Data Collection and Variables

I collect daily stock return data from 2023 to 2025 for a set of publicly traded companies. These include both treatment group stocks (e.g., DIS, DKNG, PARA, COF), which are directly involved in the sports or entertainment sectors, and control group stocks (e.g., MSFT, WMT, V, JNJ), which are unrelated to sports and less likely to be affected by March Madness.

- Game Day Indicator: A binary variable equal to 1 if the date corresponds to a scheduled NCAA March Madness game.
- Return: Daily log return of each stock.
- VaR (90%): Value-at-Risk is calculated using a rolling quantile method with a window of 100 trading days. A violation is recorded if the actual return is lower than the predicted VaR.
- Violation: A binary outcome indicating whether a VaR breach occurred.
- Group: A categorical label assigned based on whether the stock belongs to the treatment or control group.

3.3 Post-Event Violation Windows

To assess whether the effect of game days extends beyond the event itself, I analyze the occurrence of VaR violations in the following days. I create rolling windows from 1 to 10 trading days after each game day and calculate the average number of violations within each window, adjusted by the window length.

Using AIPW estimation, I evaluate how the likelihood of violations changes across different time horizons. The results suggest that the distraction effect gradually increases over time, with higher average violation rates observed in longer post-event windows.

3.4 Propensity Score Estimation

To control for potential confounding variables, I estimate the propensity score for being treated on a given day using a logistic regression model. Covariates in the model include lagged return and five-day rolling volatility. This approach helps ensure that the comparison between treated and untreated observations is based on similar risk profiles and return histories.

3.5 Augmented Inverse Probability Weighting (AIPW)

To estimate the causal effect of treatment (being a game day) on the probability or frequency of VaR violations, I implement the AIPW estimator. This method combines inverse probability weighting with outcome regression to adjust for both treatment assignment and outcome model misspecification. AIPW is particularly useful in this context because it provides double robustness—the estimator remains consistent if either the treatment model or the outcome model is correctly specified.

3.6 Augmented Inverse Probability Weighting (AIPW)

I generate a series of time series plots to illustrate return and VaR trajectories across companies, with clear markers indicating game days and violation events. Bar plots are also used to compare the average violation rates across treatment and control groups, for both immediate and post-event periods. These visualizations are supplemented with statistical tests and AIPW estimates to support conclusions.

4 Results

4.1 Descriptive Visualization of VaR Violations

To begin the analysis, I visualize the daily return patterns against the 90% Value-at-Risk (VaR) threshold for all stocks in the treatment and control groups. In Figures 4.1 and 4.2, each stock's return time series is plotted alongside the corresponding VaR threshold. Game Days are annotated with vertical green lines, while violations (instances when returns fall below the VaR threshold) are highlighted in red dots.

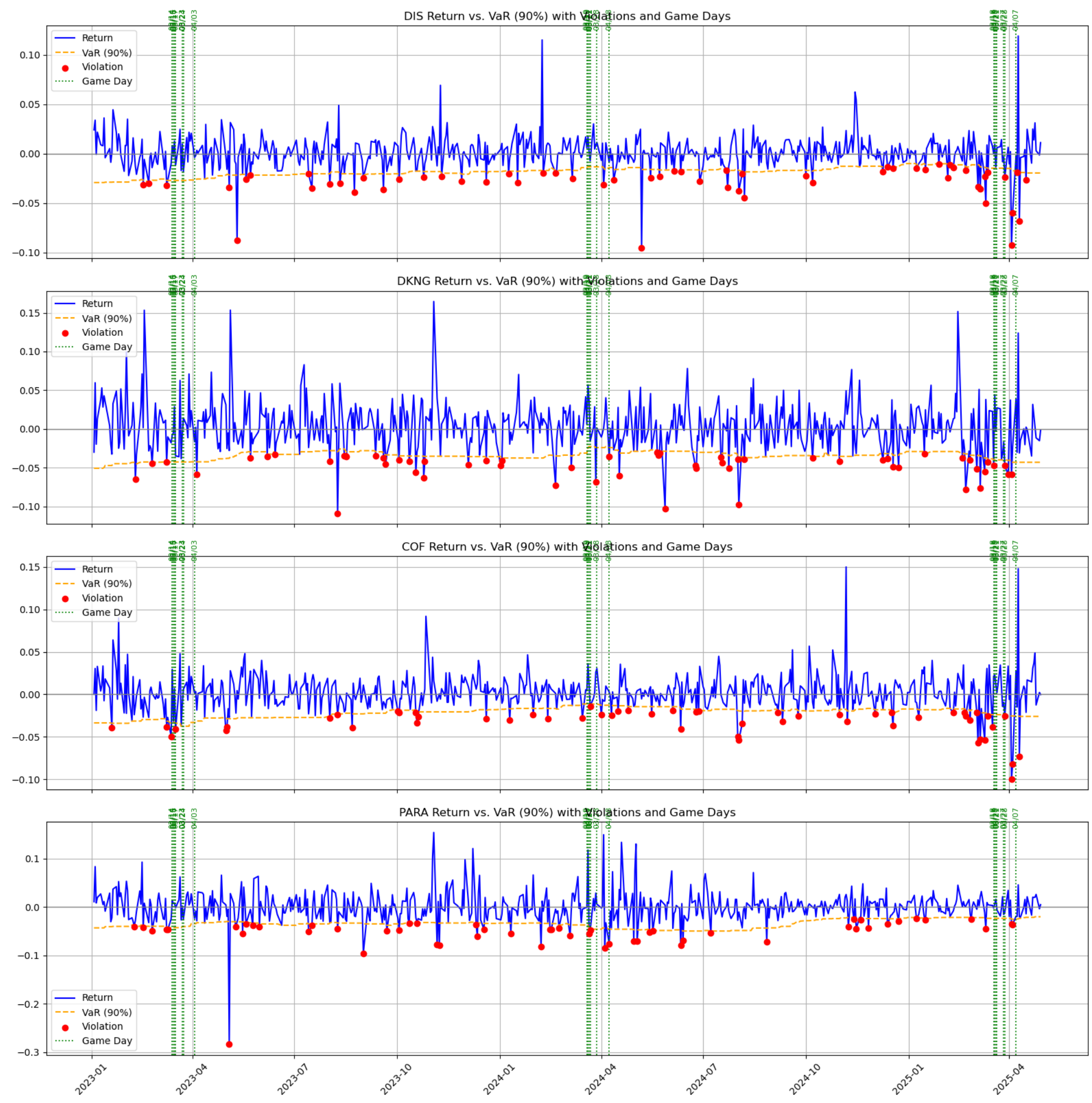

Figure 4.1. Daily returns and 90% VaR thresholds for treatment group stocks (DIS, DKNG, COF, PARA)

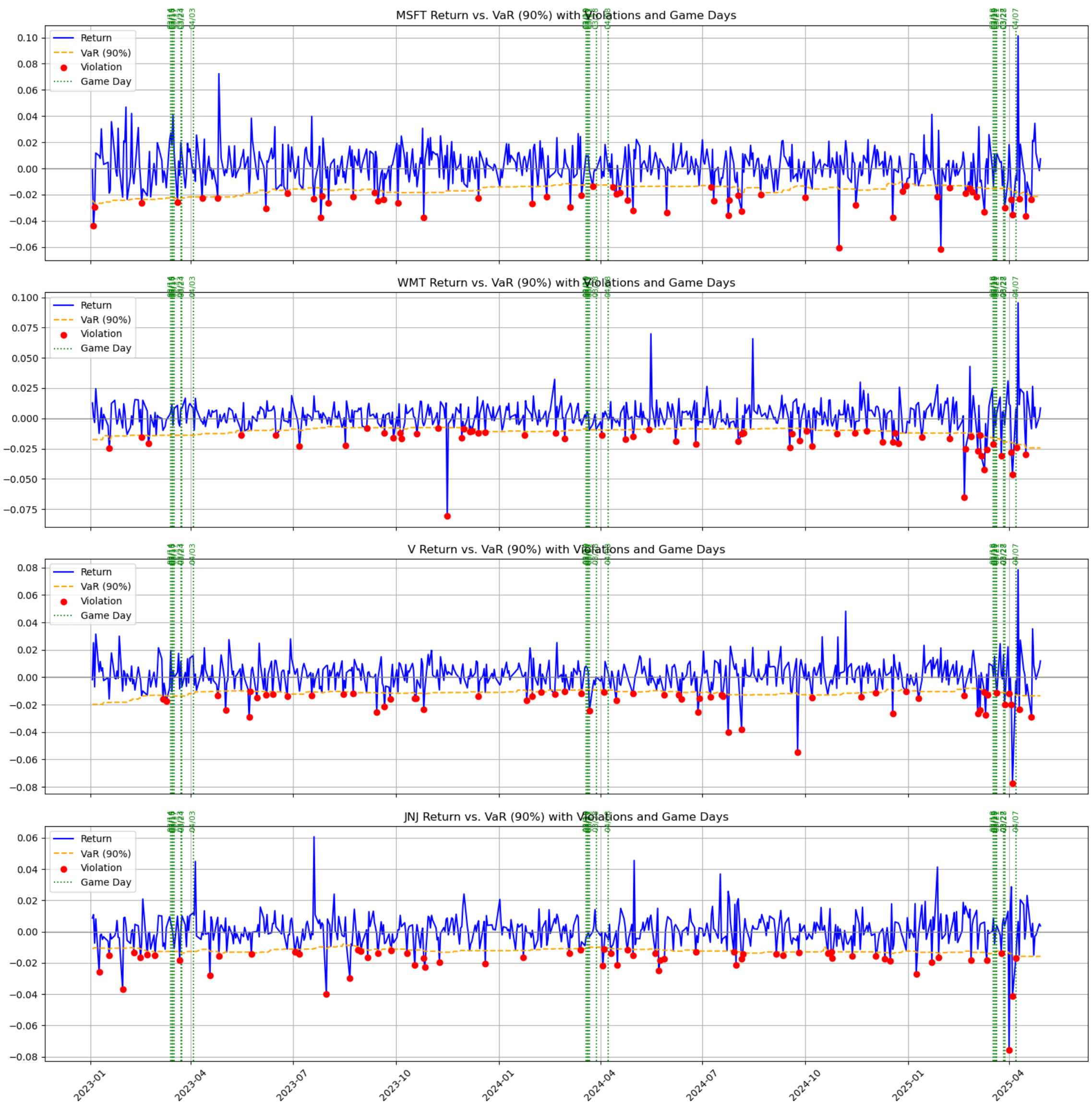

Figure 4.2. Daily returns and 90% VaR thresholds for control group stocks (MSFT, WMT, V, JNJ)

At a visual level, it is not straightforward to determine whether violations are systematically related to Game Days. While violations do occur near Game Days in both treatment and control stocks, there is no immediately obvious concentration or divergence that can be reliably discerned by eye. Therefore, these plots are intended to provide descriptive context and support subsequent formal analysis, rather than serving as conclusive evidence.

4.2 Propensity Score Distribution

Before estimating treatment effects, I examine whether the treatment group (Game Day observations) and the control group (Non-Game Day observations) share a sufficiently overlapping distribution in terms of their estimated propensity scores. This step is crucial because causal inference methods such as Augmented Inverse Probability Weighting (AIPW) rely on the assumption of common support—that is, for each unit in the treatment group, there must exist a comparable unit in the control group with a similar likelihood of treatment given observable covariates.

Figure 4.3 displays the density distributions of the estimated propensity scores for both groups. Conceptually, propensity scores act as a balancing tool: they summarize multiple covariates into a single metric that reflects the probability of being treated. By comparing these scores, I can assess whether observed differences in outcomes are attributable to the treatment itself or to underlying disparities in characteristics.

The figure shows a reasonable degree of overlap between the two groups, indicating that it is plausible to compare treated and untreated units under the AIPW framework. While some minor imbalance is visible on the left tail, the shared region is sufficiently broad to proceed with the estimation. This visual diagnostic helps establish the credibility of the causal claims that follow.

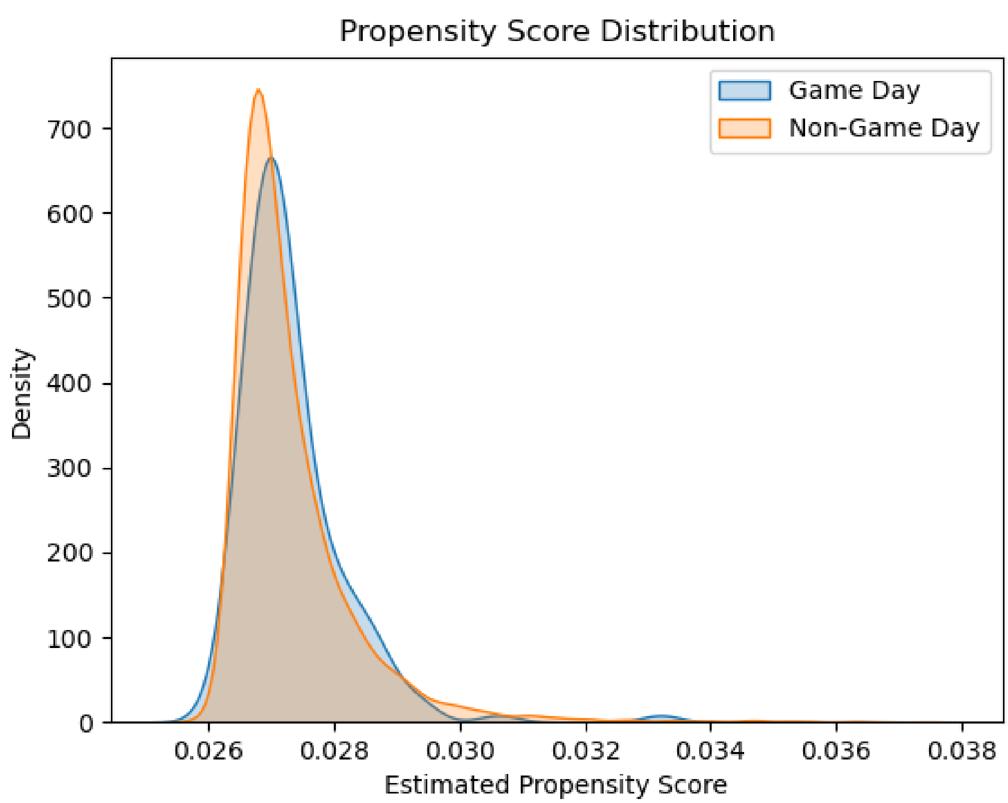

Figure 4.3. Estimated propensity score distribution for Game Day vs. Non-Game Day observations, showing sufficient overlap for causal analysis.

4.3 Average Treatment Effect of Game Days on Violation Probability

I then estimate the causal effect of Game Day on the probability of VaR violations. Figure 4.4 presenthe AIPW method across different post-event time windows. The probability of violation increases with the length of the window, from 1-day to 10-day periods.

For example, in the 3-day window after a Game Day, the violation probability increases by approximately 6.77 percentage points. By the 10-day window, the estimated increase reaches 15.52 percentage points. This suggests a cumulative effect of Game Day distraction on post-event risk management failures.

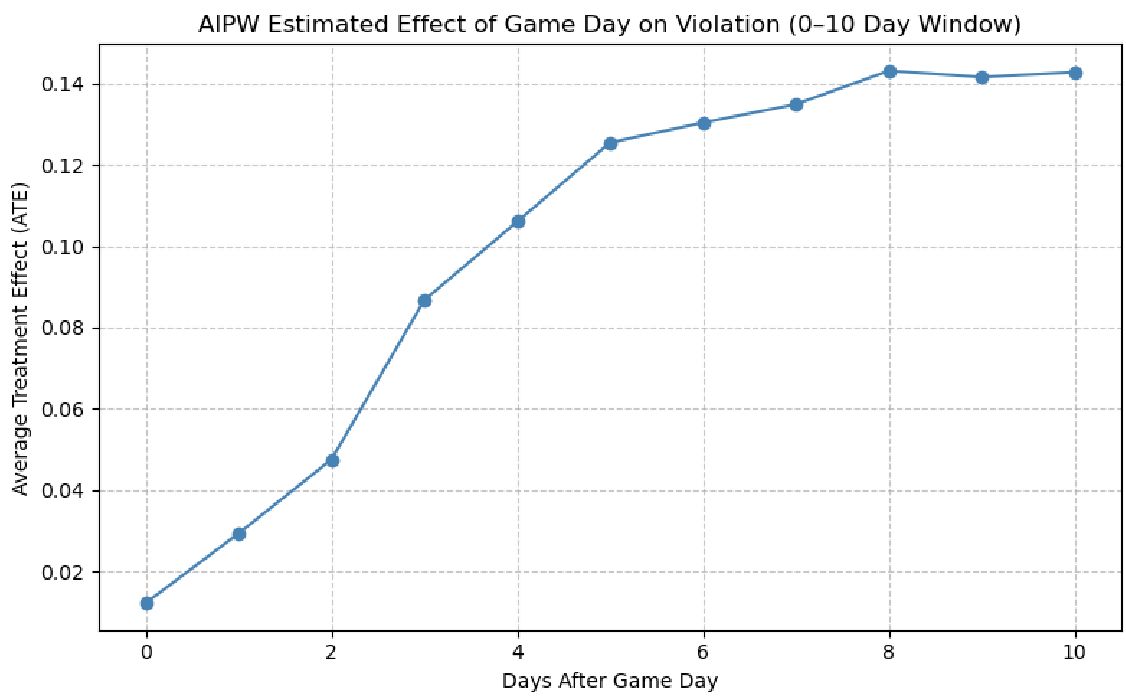

Figure 4.4. AIPW-estimated Average Treatment Effect (ATE) of Game Day on violation probability across different post-event time windows (0–10 days).

4.4 Post-Event Violation Intensity

Instead of just examining whether any violation occurs, I also analyze how many violations happen on average after a Game Day. Figure 4.5 shows the estimated ATE of Game Day on the average number of violations within a 1- to 10-day period, adjusted by the size of the window.

The effect is monotonic: Game Days are associated with more violations per day in the post-period. For instance, the 5-day window results in 0.032 extra violations per day, and this grows to 0.0435 per day in the 10-day window. This suggests not only a higher chance of any violation but also a greater intensity of risk management failures.

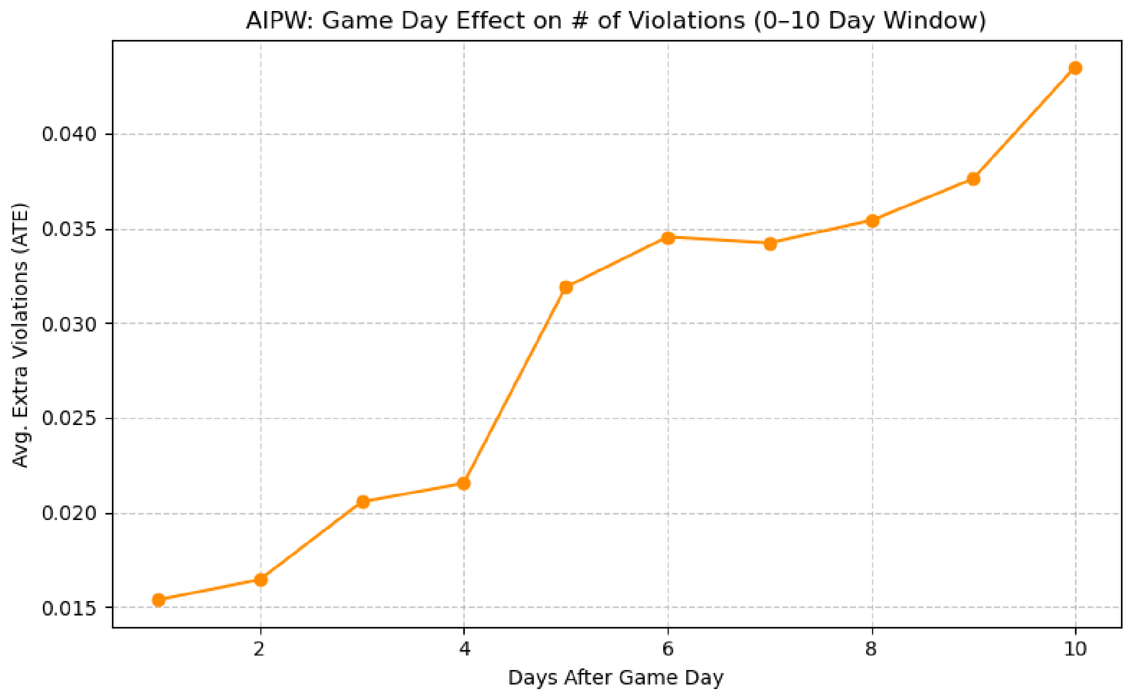

Figure 4.5. AIPW-estimated effect of Game Day on the average number of violations per day within a 1–10 day window.

4.5 Group-Based Comparison

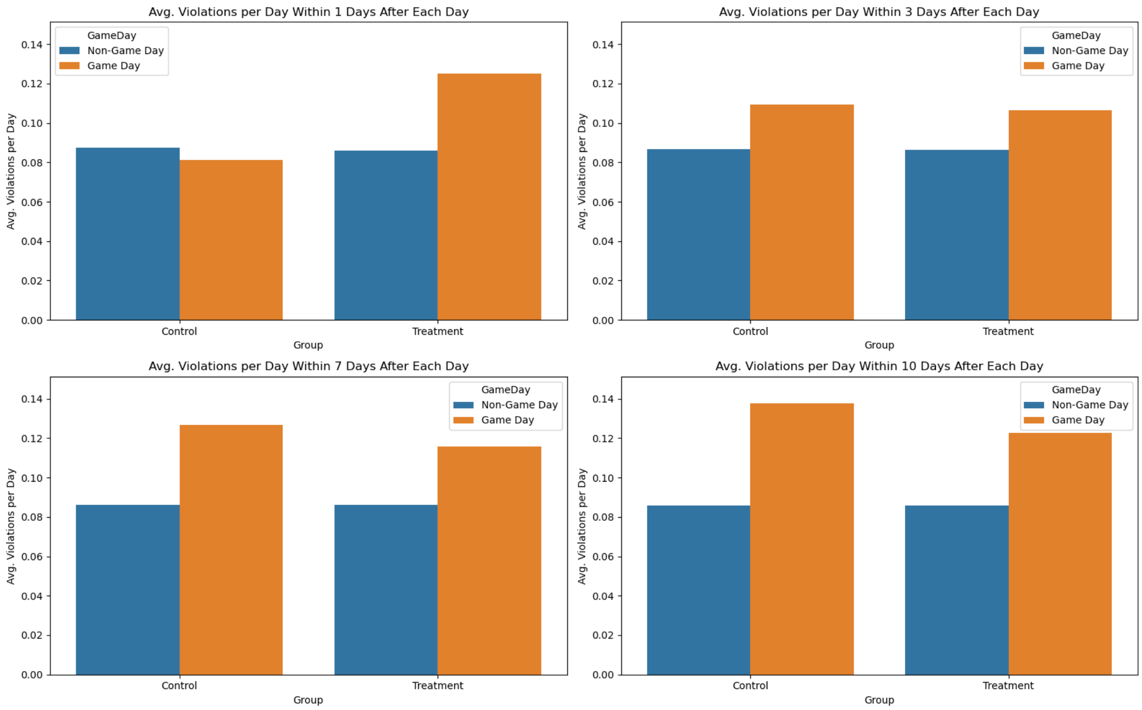

Figure 4.6. Bar charts comparing average violations per day between Game Day and Non-Game Day periods, separately for control and treatment groups. The treatment group shows consistently higher post-event violations.

To further validate these findings, I conduct a detailed group-level comparison of average daily violation rates. Figure 4.6 illustrates the average number of VaR violations per day within 1, 3, 7, and 10 days after a Game Day, segmented by Game Day and Non-Game Day and shown separately for the treatment and control groups.

From the 1-day window, the treatment group exhibits a distinctly higher violation rate on Game Days compared to Non-Game Days. This elevated risk persists in the 3-day window, although the gap begins to narrow. By the 7-day window, an interesting reversal occurs: the control group slightly surpasses the treatment group in average daily violations. However, the magnitude of this difference remains small. This may suggest potential latent differences in violation tendencies between groups, but does not significantly alter the core insight.

Across all time windows, the difference between Game Day and Non-Game Day violation rates is more pronounced than the difference between treatment and control groups. This reinforces the notion that emotionally charged events such as NCAA March Madness influence risk-related outcomes regardless of firm classification.

4.6 Post-Event Violation Intensity

For completeness, I compare the unconditional average VaR violation rate across all treatment and control firms, regardless of event timing. Figure 4.7 displays this summary. Both groups exhibit similar overall violation rates, suggesting that their baseline risk profiles are comparable. This further strengthens the interpretation that observed effects in prior figures are not driven by inherent differences in firm behavior, but rather by event-driven variation.

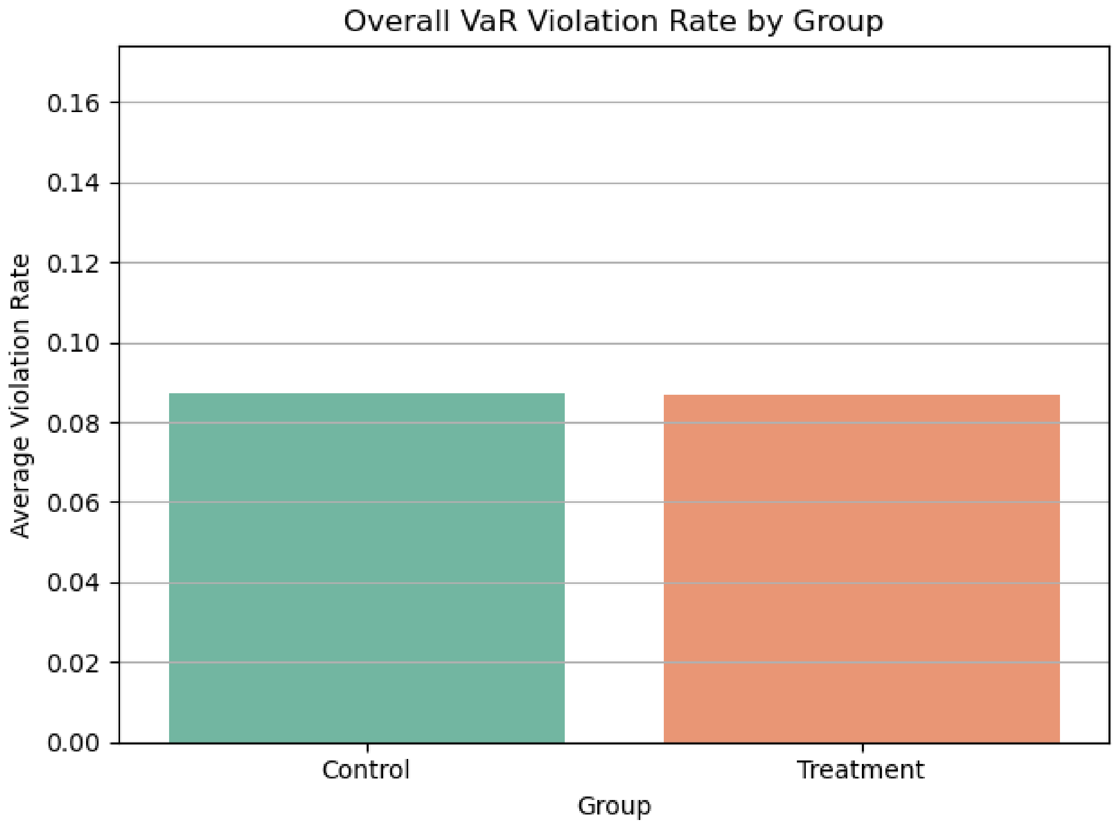

Figure 4.7. Comparison of the average VaR violation rate between the treatment and control groups.

5 Discussion

5.1 Interpretation of Key Findings

The analysis reveals a consistent pattern in which firms exposed to NCAA March Madness Game Days are more prone to risk management failures, as measured by VaR violations. Causal inference using the Augmented Inverse Probability Weighting (AIPW) method indicates that Game Days lead to statistically meaningful increases in both the probability and intensity of violations, with the effect gradually building over a 10-day post-event window.

This causal signal is reinforced by group-based comparisons. In particular, the 1-day window shows that treatment group firms have a clearly higher average violation rate on Game Days compared to Non-Game Days, suggesting an immediate short-term impact. However, in longer windows such as 7 days, the control group occasionally shows similar or even higher violation rates, possibly reflecting underlying firm heterogeneity or random variation. Despite these fluctuations, the overall pattern remains consistent: emotionally salient events are associated with an elevated likelihood and frequency of risk violations, especially in the short run.

5.2 Robustness and Limitations

Despite the use of a robust causal identification strategy via AIPW and propensity score balancing, several limitations remain. First, the observational nature of the data means that unmeasured confounders may still exist, particularly factors that simultaneously influence media exposure and market volatility.

Second, the choice of firms in the treatment group, although based on logical criteria (e.g., direct sponsorships, advertisement exposure), may introduce classification errors. Some firms classified as 'exposed' may not experience meaningful attention shifts during March Madness, and vice versa.

Third, the temporal resolution is constrained to daily data. Intraday patterns could reveal more nuanced mechanisms of distraction and risk management breakdowns.

5.3 Implications for Financial Risk Management

The findings highlight an important behavioral dimension of risk management: attention is a limited resource. When managerial or market attention is diverted by external events, even those unrelated to firm fundamentals, the likelihood of violations in pre-specified risk thresholds increases. This has direct implications for how firms and regulators design monitoring systems. For example, dynamic adjustments to oversight intensity during known periods of distraction may be warranted.

From a portfolio management perspective, the study suggests that investors may also benefit from awareness of collective attention shifts. Periods like March Madness may serve as implicit risk signals, not because of fundamental shifts in valuation, but because of systematic behavioral patterns.

5.4 Suggestions for Future Research

Future work may enhance this research by leveraging higher-frequency data (e.g., hourly returns) to observe the precise timing and dynamics of post-event violations. Additionally, alternative definitions of treatment—such as sentiment scores, regional media coverage, or firm-specific engagement metrics—could provide a richer view of exposure.

Moreover, integrating machine learning-based heterogeneity analysis may help identify firm characteristics that make some entities more vulnerable to distraction-induced risk failures. Finally, extending the analysis beyond March Madness to other emotionally salient periods (e.g., elections, major sports events) could further generalize the findings.

5.5 Final Remarks

This study bridges behavioral finance with operational risk management, showing how non-fundamental, attention-grabbing events can subtly but measurably affect firm-level risk adherence. In doing so, it opens new pathways for both academic research and practical monitoring frameworks.

6 Discussion

This study investigates whether emotionally salient events, specifically NCAA March Madness Game Days, affect firms’ adherence to financial risk protocols, using Value-at-Risk (VaR) violations as the primary measure. Through a combination of descriptive visualizations and causal inference methods, the analysis provides evidence that attention-diverting events can lead to increased risk management failures in publicly traded firms.

The findings from the Augmented Inverse Probability Weighting (AIPW) method show that Game Days are associated with statistically significant increases in both the probability and average intensity of VaR violations, with the effect intensifying over time and peaking within a 10-day post-event window. These results support the hypothesis that emotionally charged events can disrupt operational discipline in risk-sensitive environments.

This pattern is further supported by group-level comparisons, especially in the immediate aftermath of Game Days. For example, in the 1-day window following a Game Day, firms in the treatment group exhibit noticeably higher violation rates than on other days, indicating a short-term behavioral response to distraction. However, longer windows such as 7 or 10 days reveal mixed results, with some instances where the control group shows comparable or even higher violation rates. These inconsistencies may reflect firm-level heterogeneity or limits in exposure classification.

Despite these variations, the core insight remains robust: Game Days introduce a measurable disturbance in firms' risk behavior, highlighting the behavioral component of financial risk management. Attention is not infinite, and when external events draw cognitive resources away, the ability to uphold standard risk controls can degrade, even in the absence of fundamental changes in firm value.

These findings carry several implications. From a practical standpoint, firms and regulators may need to account for known attention shocks when evaluating risk exposure. For investors, periods like March Madness may serve as behavioral risk indicators, not because of intrinsic financial relevance, but due to their potential to alter collective attention and decision-making behavior.

Future research could expand on these results by incorporating higher-frequency return data or alternative definitions of exposure based on media intensity or individual-level sentiment. Exploring firm-specific traits that influence susceptibility to distraction could also deepen our understanding of operational risk in noisy environments. Finally, extending this approach to other events, such as political elections or global sports tournaments, could generalize the behavioral risks observed in this study.

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