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The Effect of New York City Sports Outcomes on the Stock Market

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Abstract

This thesis investigates whether sports outcomes for New York City based teams affect the daily returns, volatility or trading volume of major stock indexes in the United States. I research whether events that affect local mood in a major financial center can influence national stock indexes by swaying the sentiment of workers in the financial sector. By performing an event study I found evidence that returns are abnormally high following championships won by New York City professional sports teams. Returns are abnormally low and volume is abnormally high following elimination from a championship round.

Keywords

Stock Market, Sports, Behavioral Economics, Investor Sentiment, Volatility, Event Study

Cover Page Footnote

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I. Introduction/ Literature Review

In writing this paper I examine whether sports outcomes for teams based in New York City have an effect on the daily returns, volatility or trading volume of major stock indexes in the United States. Sports affect mood, and mood in turn can impact an individual's decision making. Financial analysts can influence stocks' behavior through their recommendations by generating a temporary buying or selling pressure. As a result, events that affect local mood like New York City sports outcomes can influence major stock indexes by swaying the sentiment of financial analysts and traders.

A great deal of recent literature in behavioral economics has examined the connection between investor sentiment and asset pricing. Lowenstein (2000) has claimed that visceral factors such as negative emotions and feelings have an impact on economic decision-making. As a result, people do not always base their decisions on solely rational factors. Rather than behaving in ways dictated by careful consideration of the costs and benefits of an action, individuals' behavior is often motivated by emotions. Among the factors that cause misvaluation and bias of security prices are heuristic simplification, whereby a person bases decisions on limited information that is available and easy for him to process, overconfidence in one's ability and knowledge, and emotions including a distaste for ambiguity. In particular, mood affects abstract judgment rather than areas on which a person has specific information (Hirshleifer 2001). Researchers find that there is a strong correlation between hours of daylight for a country, and stock market index returns for the country's stock exchange, which they attribute to investor psychology. Seasonal affective disorder, a condition affecting humans during phases in which hours of daylight are low, is linked to depression, and depression is strongly related to risk aversion. As a result, seasonal differences in hours of daylight can generate differences in seasonal stock variation (Kamstra, Kramer and Levi 2003). Other research papers in economics have investigated the impact of various factors on asset prices through the investor sentiment effect. Yuan et al (2002) examine whether lunar cycles impact stock returns. They base the research on, among other things, psychology literature demonstrating a tie between the lunar and menstrual cycles, along with research showing that crimes occur at a higher rate during full moons. They find that stock returns are lower when there is a full moon than on days when there is a new moon. This difference, whose cause researchers attribute to investor mood, amounts to approximately 4.2% per annum. Additionally, they find that the lunar effect is greater for small cap stocks than for large cap stocks. Cao and Wei (2004) investigate whether temperature has an effect on the stock market.

In the field of psychology, literature has investigated whether sporting event outcomes are an important determinant of mood. Wann (1994) found that fans experience negative emotions after losses and positive emotions after victories by their favorite teams. Bizman and Yinon (2002) discovered that after basketball games, fans of winning teams had higher self-esteem and more positive emotions than they did before the games, while after losses, fans had lower self-esteem and more negative emotions than before the games. Schwartz (1987) found that the results of two of Germany's games in the 1982 World Cup affected fans' view of their own welfare and issues of national importance. This finding suggests that sports outcomes affect individuals' optimism and outlook on life, important determinants of investor's stock market decision making. Schweitzer et al (1992) surveyed football fans during a game for their appraisal of the likelihood of a war in Iraq in 1990 and the potential casualties in such a war. He found that the probability of war and number of potential casualties predicted was lower among fans of a winning football team than fans of a losing football team. Arkes, Herren, and Isen (1988) determined that following a win by the football team of the Ohio State University, sales of lottery tickets in the state of Ohio increase.

A large body of research has suggested that there is an excess return correlated with financial analysts' recommendations. Barber and Loeffler (1993) study the effect that analysts' recommendations have on stock prices and volumes. They determine that analyst recommendations cause abnormal returns in stock prices on atypically heavy volume, and that half of this return is eventually reversed. Their findings support the *price pressure hypothesis*, which states that analyst recommendations generate a temporary buying pressure by naive investors who rush to buy the recommended stocks, and therefore create an abnormal return, which is eventually reversed if the analysts did not reveal any new relevant information to the public. Han and Suk (1996) expand on these findings, and similarly determine that analyst recommendations generate a temporary market reaction and subsequent reversal consistent with the price pressure hypothesis. Based on this research, if a mood variable were to affect the psychology of financial analysts, and hence affect their recommendations, it could potentially move the stock market by generating a reaction as predicted by the price pressure hypothesis.

Saunders (1993) studied the relationship between New York City weather and daily changes in major stock market indexes. He determined that sunny and cloudy weather in New York City does impact stock prices, and concluded that stock prices are not wholly a function of economically pertinent new information. Saunders claimed that those who trade listed stocks on Wall Street may have their mood affected by weather. He wrote that because they always assemble at the same location, these traders' decisions could be affected by a local mood variable. Hence, because analyst recommendations and traders' behavior can impact broad stock indexes, a local mood variable has the potential to affect stock returns for major indexes. By using major market indexes rather than individual stocks, Saunders eliminates the possibility that the local weather will have a direct effect on the factors of production and thus on the specific stocks. In doing so he is able to ensure that any market reaction caused by New York City weather would be driven solely by trader sentiment. In my research, I too use major market indexes in order to ensure that New York sports outcomes would not impact the fundamental valuation of the stocks I consider. Such a diversification ensures that a rationally priced index should not respond to a biased sample of local news, such as weather, or local sporting outcomes.

Existing research that examines the impact of local sporting outcomes on asset prices, determines what the impacts of those outcomes are on locally headquartered stocks, rather than on major indexes. My research is different in that it investigates how local sporting outcomes affect national stock indexes. Chang et al (2012) performed a firm-level analysis to determine whether NFL game outcomes affect the stocks of companies headquartered near the teams' stadiums. Recent literature examines the impact that national sporting results have on a nation's stock market through the investor sentiment effect. Ashton et al (2003) determine whether the London stock exchange was affected by England's national soccer team's performance in international matches. The authors list two primary explanations for why the stock market could be impacted by the performance of England's national team. The first is the "feelgood" factor caused by national sporting success, which leads to greater confidence about the future. The second is that due to the growing commercial significance of international tournaments, an efficient market would revise expectations of the potential economic benefit of progressing further in an international soccer tournament. In my research, as stated previously, there is no reason to expect that New York sports outcomes would have an economic impact on an entire market index. Therefore I am able to single out the investor sentiment effect as the sole conduit through which New York sports outcomes could affect the major stock indexes.

Edmans et al (2007) used international soccer results in 39 different countries to investigate the effect of investor sentiment on asset prices. According to the authors, a mood variable must satisfy three characteristics in order to rationalize the link to stock returns. The first is that it must drive investors' mood in a substantial and unambiguous way so that its effect is powerful enough to show up in asset prices. The second is that it must impact the mood of a large proportion of the population in order to affect enough investors. The third is that it must be correlated across the majority of individuals within a country. The authors claim that international soccer satisfies these conditions, however performance of New York sports teams would not meet the second and third conditions, unless a very high percentage of investors in the stock exchange in the United States were New York sports fans.

On the other hand, many of the brokers and analysts are located in New York, and their mood after a win or loss by one of their favorite teams could affect the recommendations that they give to their clients, who are located across the globe. As Barber and Loeffler (1993) showed, financial analyst recommendations have been shown to drive changes in stock prices. As a result, the majority of investors in the country would not need to be impacted by the local mood variable, and it would be sufficient for traders and financial analysts to have their sentiment swayed by the New York sporting outcomes in order to have an effect on the stock market.

Some researchers find that happy people become more optimistic and more confident, while negative emotions make people more pessimistic. Inducing negative emotions in test participants by showing them a newspaper description of a tragic event increased the participants' estimate of probability of risks and adverse outcomes. These subjects would thus become more risk averse. Positive emotions induced by recounting happy events yielded a decreased estimation of risk probability (Johnson and Tversky 1983). Based on this literature, it appears that important victories by New York sports teams should result in increased risk taking, and hence higher stock market volatility, while losses should lead investors to be more risk averse, and therefore reduce volatility. Additionally, because victories would make subjects more optimistic, this theory suggests that victories should result in higher returns as well. Losses, which would make people more pessimistic, and should therefore result in lower stock returns.

Other researchers believe that positive affect influences utility of losses. They explain that happy people strive to maintain their happy feelings and positive emotions. They therefore associate more negative utility with losses than control groups do (Isen and Simmonds 1978). The utility curve for subjects with induced positive emotions is steeper in the losses end than that of control subjects. As a result, people who are feeling good are more sensitive to losses (Isen, Nguyen, Ashby 1988). As a result positive affect causes a phenomenon known as cautious optimism. Those who have had positive affect induced overestimate the probability of winning and underestimate the probability of losing, while control groups do not. At the same time, however, in gambling situations where they may suffer an actual loss, positive affect groups are more cautious and less likely to gamble. They bet less than control groups when probability of loss is small but potential loss is large, while they bet more when potential loss is small although probability is larger. These findings suggest that when induced with positive emotions individuals perceive a greater loss of utility. Thus a loss would be greater for a happy person than for one in a neutral state (Isen, Nguyen, Dulin 1996). While induced positive emotions cause individuals to act in a more risk averse manner in order to maintain the positive emotions, negative emotions generate more risk taking behavior in order to restore utility (Zhao 2006). Negative emotions such as embarrassment and anger can result in increased risk taking. When people are upset they are more likely to select high-risk, high-reward choices in an attempt to alter their state of mind. The subjective utility of a good outcome becomes larger for those induced with negative emotions, while the costs of a loss are reduced. (Leith and Baumeister 1996). Researchers find that people whose emotional condition is negative are more likely to systematically engage in risky behavior than those with a positive condition (Chuang and Lin 2007). The aforementioned literature suggests an alternate theory that victories by New York sports teams should result in decreased risk taking and hence a lower volatility, while losses would increase risk taking and thus resulted in elevated levels of volatility. By testing whether New York City sporting outcomes affect stock market volatility, as measured by the VIX, I seek to test which of the two theories regarding the effect of positive or negative emotions on risk taking is valid.

My contribution to existing literature is in determining whether sports outcomes at the local level, in a major financial center where a substantial number of analysts and traders reside, can impact stock returns or volatility at the national level, by influencing the behavior of financial analysts. Another contribution that I make to existing literature is in determining how sports events and outcomes affect stock market volatility through the investor sentiment effect. Based on the aforementioned literature, I hypothesize that important victories by New York City sports teams should cause returns to be abnormally high, while crucial losses should lead to abnormally low returns. I also test the two disparate theories regarding the effect of emotions on risk taking. The first would expect that victories should cause increased optimism and confidence, and hence generate increased risk taking evidenced by higher market volatility. Losses would have the opposite effect. The second theory would expect that championships won or important victories by New York teams in playoff games would lead to decreased risk taking due to individuals trying to maintain their positive mood, and hence a lower volatility in stock returns. Important losses would result in increased risk taking, and hence a high volatility. Many empirical papers show evidence that suggests that there is a positive and statistically significant relationship that exists between volatility and trading volume for major indexes. Mahajan and Singh (2008) exhibit evidence that this positive and significant correlation between volume and return volatility exists using daily data on the SENSEX (the index for the Bombay Stock Exchange) between 1996 and 2006. Lee and Rui (2002) have a similar finding for the S&P500, and determine that volume has a positive feedback effect on return volatility. I therefore seek to confirm volatility results with data on stock volume.

II. Data

The data on sports outcomes for the New York City professional sports teams from November 1, 1949 through September 10, 2014 is collected from sports-reference.com. The data collected includes both regular season and postseason results of games played by the New York Yankees, New York Mets, New York Knicks, Brooklyn Nets (including their games played as the New Jersey Nets), New York Rangers, New York Islanders, New York Giants and New York Jets.

A total of 13,793 wins by New York City sports teams, and a total of 13,300 losses were collected. 765 of the wins occurred in the playoffs, while 724 of the losses occurred in the playoffs. Due to the high frequency of regular season games played by the professional sports teams, I have determined that it is far more likely that the outcome of a postseason game would have a substantial effect on investor's mood, and therefore used only the playoff outcomes in my analysis. Additionally there were 31 championships won by the New York City teams during the time span, and 27 occurrences of elimination from the championship stage.

The data on daily stock returns for the Dow Jones Industrial Average (DJIA), Nasdaq Composite, New York Stock Exchange Composite Index (NYSE), and S&P 500 is derived from Datastream. I matched these daily stock returns with the previous day's games. This data dates are far back as May 5, 1950 and runs through September 10, 2014. Data on the S&P600, S&P100 and VIX along with data on daily trading volume for the S&P 500, NYSE, DJIA, S&P100, S&P600 and Nasdaq were taken from Bloomberg.

The number of observations for playoff games by each team are found below.

	# of Playoff Wins	# of Playoff Losses	# of Total Playoff Games
Yankees	166	123	289
Mets	43	31	74
Rangers	157	181	338
Islanders	134	106	240
Knicks	180	182	362
Nets	97	109	206
Giants	22	17	39
Jets	12	13	25

III. Methodology and Results

In order to determine how the outcomes of playoff games for the New York sports teams affected stock returns for major indexes, I ran several Ordinary Least Squares Regressions as follows:

Equation #1:

$$R_t = \alpha + \beta_1 R_{t-1} + \sum_{i=1}^{11} \delta_i M_{it} + \sum_{i=1}^{6} \theta_i D_{it} + \sum_{i=1}^{8} (\pi_i W_{it} + \varphi_i L_{it}) + \rho y_t + \varepsilon_t$$

R_t represents the daily stock return for an index and R_{t-1} is the previous trading day's daily return, which was included in the regression because daily time series demonstrate high degrees of statistical dependence as shown by Akgiray (1989).
M_i are dummy variables for the months of the year, and D_i are dummy variables for day of the week. y_t is a variable used to indicate the year, in order to adjust for inflation. W_i are dummy variables each of which signifies a playoff win by a different New York sports teams in the previous day. L_i are dummy variables each of which signifies a playoff loss by a different New York sports teams in the previous day.

Additionally, the following regression was also used to determine whether stock returns for major indexes were affected by New York City sports games.

Equation #2:

$$R_t = \alpha + \beta_1 R_{t-1} + \sum_{i=1}^{11} \delta_i M_{it} + \sum_{i=1}^{6} \theta_i D_{it} + \pi C_t + \sigma E_t + \rho y_t + \varepsilon_t$$

Equation #3:

$$R_t = \alpha + \beta_1 R_{t-1} + \sum_{i=1}^{11} \delta_i M_{it} + \sum_{i=1}^{6} \theta_i D_{it} + \pi W_t + \sigma L_t + \rho y_t + \varepsilon_t$$

In this regression W is a dummy variable that represents a playoff win by any of the eight major New York City sports teams in the previous day, L is a dummy variable that represents a playoff loss by any of the eight major New York City sports teams in the previous day, C is a dummy variable that represents a championship won by any of the eight major New York City sports teams in the previous day, and E is a dummy variable that represents a loss eliminating a New York team from the final round of the playoffs in the previous day.

These regressions were run on the daily return of the S&P500, Nasdaq, NYSE, and DJIA. The regressions were also run on the S&P100, an index that tracks large capitalization stocks, and the S&P600, which tracks small capitalization stocks, in order to determine whether market capitalization affects the impact of the investor sentiment effect. None of the sports variables were found to have a statistically significant effect on the index returns, even at the 10% level. The results of the regressions can be found in the appendix, where they are expressed in terms of percentage points.

The VIX, which measures the implied volatility of S&P500 index options, was used in order to determine whether New York City playoff games affect market volatility as predicted by the literature. I decided not to run regressions on the value of the VIX, because any results would yield the interpretation that the volatility after wins or losses is different from the average volatility over the last 30 years. This interpretation would not demonstrate that wins or losses caused a change in volatility, which is the interpretation needed to test the hypothesis. As a result, I instead ran regressions on the change in the value of the VIX from the previous trading day, the percentage change in the value of the VIX from the previous trading day, and the difference between the value of the VIX and its 60-day moving average. A regression run on the spread between the VIX and its moving average would, for example, demonstrate whether volatility is higher or lower following playoff games than it has been in the recent past. The regressions listed below were also run on the percentage change in daily trading volume of the NYSE, S&P500, DJIA, Nasdaq, S&P100 and S&P600. The variables in these regressions are identical to those found in the previous set of regressions, with the exception that V_t measures either the change in the value of the VIX from the previous trading day, the percentage change in the value of the VIX from the previous trading day, the difference between the value of the VIX and its 60-day moving average, or the percentage change in trading volume from the previous trading day for the various indexes.

Equation #4:

$$V_t = \alpha + \sum_{i=1}^{11} \delta_i M_{it} + \sum_{i=1}^{6} \theta_i D_{it} + \sum_{i=1}^{8} (\pi_i W_{it} + \varphi_i L_{it}) + \rho y_t + \varepsilon_t$$

Equation #5:

$$V_t = \alpha + \sum_{i=1}^{11} \delta_i M_{it} + \sum_{i=1}^{6} \theta_i D_{it} + \pi C_t + \sigma E_t + \rho y_t + \varepsilon_t$$

Equation #6:

$$V_t = \alpha + \sum_{i=1}^{11} \delta_i M_{it} + \sum_{i=1}^{6} \theta_i D_{it} + \pi W_t + \sigma L_t + \rho y_t + \varepsilon_t$$

When regression #4 was run on the percentage change in daily volume of the DJIA, the Yankees Playoff loss variable was found to be statistically significant at the 10% level. The coefficient for this variable was 8.713. This coefficient can be interpreted as the percentage change in volume of the DJIA from the previous trading day being 8.713 percentage points higher on days when the Yankees lose a playoff game than it is on days when the Yankees do not lose playoff games, adjusting for the year, month and day of the week. None of the other regressions run on the measures of volatility or on the trading volume for the various indexes revealed that the sports variables were statistically significant effect, even at the 10% level. Results of the regressions can be found in the appendix.

I followed this approach by performing an event study where the event was a championship won by one of the New York sports teams. I also performed a separate event study where the event was elimination from the championship round by one of the New York sports teams. In order to do so I followed the procedures of Campbell, Lo and Mackinlay found in The Econometrics of Financial Markets. I began by calculating the normal return for the 120 trading days before the event using the Constant-Mean-Return model $R_{it} = \mu_i + \xi_{it}$. This model was selected because the normal return of the market itself is being calculated, rather than that of an individual stock. Additionally, it has been found that more sophisticated models often perform no better than the Constant-Mean-Return model (Brown and Warner 1980).

Next I calculated the daily abnormal return following the event $\varepsilon_{it} = R_{it} - \mu$ where R is the actual return and μ is the normal return. I then calculated the cumulative abnormal return (CAR) by taking the arithmetic average of all daily abnormal returns over specified post-event windows of lengths varying between 1 and 30 days. Finally, I ran a T-test to determine whether the cumulative abnormal return is statistically significant.

I performed the event study on the Dow Jones, S&P500, Nasdaq, NYSE, S&P600, S&P100, VIX, Dow Jones Volume, S&P500 Volume, S&P100 Volume, and S&P600 Volume. The event study run on the NYSE revealed that over both the 20 and 30 day windows following a championship won, there was a cumulative abnormal return of approximately 0.06% which is statistically significant at the 10% level. The event study run on the S&P500 similarly revealed that over a 20 and 30-day window following a championship, there was a cumulative abnormal return of approximately 0.07% which is statistically significant at the 10% level. The S&P100 was found to have a cumulative abnormal return of -0.82% over the 1 day period following elimination from a championship, which was statistically significant at the 5% level. The S&P600 was found to have a cumulative abnormal return of -1.14% over the 1 day period following elimination from a championship round, statistically significant at the 5% level, and a cumulative abnormal return of -0.39% over the 2 day window following elimination from a championship round, statistically significant at the 10% level. The DJIA, S&P500, S&P100 and S&P600 volumes were found to be abnormally elevated over 1 and 2 day event windows following elimination from championship rounds. This abnormal elevation in volume was found to be statistically significant at the 5% level. The event study was performed on the value of the VIX because any results would have the interpretation that there was a difference between the volatility following the event, and the average volatility prior to the event, which would be an appropriate test of the hypothesis. The volatility following the events was not found to be different from its average value prior to the events in a statistically significant way. The results of the event study can be found in the appendix with statistically significant results bolded.

IV. Conclusion

The regressions run on the measures of volatility did not reveal that sports outcomes had an effect on volatility, and neither did performing the event study on the value of the VIX.

None of the regressions run on the major stock indexes revealed that playoff results for New York City sports teams affected stock returns. The event study approach, however, revealed that over 20 and 30-day windows following championships, cumulative abnormal returns for both the NYSE and S&P500 were positive and statistically significant. The S&P100 and S&P600 revealed that over 1 and 2-day windows following elimination from championship rounds, cumulative abnormal returns were both negative and statistically significant. Based on the event study methodology, for some of the indexes the hypothesis that an event as significant as a championship by a New York City sports team would sufficiently affect the mood of analysts and drive their recommendations for stock buying, thereby generating abnormally high returns was confirmed.

When run on the volume of the DJIA, regression #4 revealed that Yankees playoff losses cause the percentage change in daily volume from the previous trading day to be higher than it would otherwise be. Based on the event study methodology, volume for the DJIA, S&P500, S&P100 and S&P600 was found to be abnormally high over the 1 and 2 day event windows following elimination from championship rounds. The results of the event study and of the regression thus support the hypothesis that trading volume and volatility, which the literature demonstrates to be positively correlated with volume for major indexes, should be higher when investors are induced with negative emotions.

There are several explanations for why statistically significant results regarding the returns were yielded through the event study, but not through the OLS regressions. The first is that perhaps the sample size used in the event study was too small. The greatest sample size used for the event studies was 31, and the smallest was 7. The second explanation is that the event study and OLS regressions have different interpretations, and measure different things. The OLS regressions on returns of the S&P500 for example, measures whether following a championship, or playoff win, the return is greater than the return is on average on days when there is not a championship or playoff win in that year. The event study, on the other hand measures whether the return following a championship is different from its average value in the near past before the championship. While these interpretations are similar, they are not identical, which may explain why the results were different depending on the methodology used.

The OLS regressions run on the returns of the S&P500 and NYSE could be biased downward, and therefore not statistically significant. The event study revealed that over 20 and 30-day windows following championships the cumulative abnormal returns for the NYSE and S&P500 were statistically significant. When this window is extended to 60, and even 120 days the cumulative abnormal returns are still statistically significant at the 10% level. Because the effect of the championship on the indices lasts for a long period of time after the event, the average return in the year in which the championship was won would be higher. As a result, the effect of a championship on the indices' returns as determined by the OLS regression would be biased downward, because the OLS regression compares the return on the day after the championship with the abnormally high average return for the indices in that year.

A falsification test was run in order to determine whether the results of the event study were spurious. An event study was performed in which Los Angeles sports championships and the elimination of Los Angeles teams from championship rounds were used as the events. The event study revealed that in no event window were the cumulative abnormal returns of the NYSE, S&P500, S&P100 and S&P600 found to be statistically significant. These findings strengthen the statistically significant results that were found when the event study was performed on the outcomes for the New York teams. The event study performed on the Los Angeles teams' outcomes did reveal that for various event windows, the volume of the S&P100, S&P600, DJIA and S&P500 was found to be abnormally high or abnormally low in a statistically significant manner. Although the sample size for these event studies was only between 2 and 6, it does bring up the possibility that the results found for the effect of New York outcomes on volume were spurious. Results of the falsification test can be found in the appendix.

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VI. Appendix

Results of Regressions on Index Returns

VARIABLES	(1) Effect on SP500 Returns	(2) Effect on SP500 Returns
SP500previousday	1.236	1.236
	(0.870)	(0.870)
NYchampionship	-0.132	
	(0.216)	
NYChampElimination	0.233	
	(0.261)	
NYCPlayoffWin		-0.030
		(0.048)
NYCPlayoffLoss		0.044
		(0.050)
Constant	-0.801	-0.794
	(1.191)	(1.192)
Observations	13,224	13,224
R-squared	0.002	0.002
Month Effect	Yes	Yes
Day Effect	Yes	Yes
Year Effect	Yes	Yes

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

VARIABLES	(1) Effect on NYSE Returns	(2) Effect on NYSE Returns
NYSEpreviousday	3.856***	3.857***
	(0.887)	(0.887)
NYchampionship	-0.128	
	(0.213)	
NYChampElimination	0.154	
	(0.266)	
NYCPlayoffWin		-0.026
		(0.047)
NYCPlayoffLoss		0.035
		(0.050)
Constant	-0.825	-0.825
	(1.248)	(1.248)
Observations	12,701	12,701
R-squared	0.004	0.004
Month Effect	Yes	Yes
Day Effect	Yes	Yes
Year Effect	Yes	Yes

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

VARIABLES	(1) Effect on DJIA Returns	(2) Effect on DJIA Returns
DJIApreviousday	2.505***	2.500***
	(0.772)	(0.772)
NYchampionship	-0.070	
	(0.170)	
NYChampElimination	0.178	
	(0.182)	
NYCPlayoffWin		-0.017
		(0.042)
NYCPlayoffLoss		0.063
		(0.044)
Constant	-0.129	-0.089
	(0.777)	(0.777)
Observations	16,787	16,787
R-squared	0.004	0.004
Month Effect	Yes	Yes
Day Effect	Yes	Yes
Year Effect	Yes	Yes

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

VARIABLES	(1) Effect on Nasdaq Returns	(2) Effect on Nasdaq Returns
Nasdaqpreviousday	4.457***	4.461***
	(0.938)	(0.938)
NYchampionship	-0.039	
	(0.281)	
NYChampElimination	0.360	
	(0.327)	
NYCPlayoffWin		0.035
		(0.060)
NYCPlayoffLoss		0.003
		(0.063)
Constant	-0.887	-0.918
	(1.812)	(1.813)
Observations	11,371	11,371
R-squared	0.007	0.007
Month Effect	Yes	Yes
Day Effect	Yes	Yes
Year Effect	Yes	Yes

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

VARIABLES	(1) Effect on SP100 Returns	(2) Effect on SP100 Returns
PreviousReturnSP100	-4.804***	-4.748***
	(1.355)	(1.355)
NYchampionship	-0.030	
	(0.383)	
NYChampElimination	-0.729	
	(0.461)	
NYCPlayoffWin		-0.003
		(0.082)
NYCPlayoffLoss		0.010
		(0.085)
Constant	-0.024	-0.026
	(2.746)	(2.747)
Observations	9,771	9,771
R-squared	0.003	0.002
Month Effect	Yes	Yes
Day Effect	Yes	Yes
Year Effect	Yes	Yes

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

VARIABLES	(1) Effect on SP600 Returns	(2) Effect on SP600 Returns
PreviousReturnSP600	-2.730**	-3.357***
	(1.386)	(1.220)
NYchampionship	0.379	
	(0.525)	
NYChampElimination	-0.459	
	(0.491)	
NYCPlayoffWin		-0.001
		(0.089)
NYCPlayoffLoss		0.033
		(0.093)
Constant	-1.678	-4.488
	(6.345)	(5.602)
Observations	5,229	5,224
R-squared	0.003	0.004
Month Effect	Yes	Yes
Day Effect	Yes	Yes
Year Effect	Yes	Yes

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Results of Regression on Volatility Index

VIX using %change in daily value of the VIX

VARIABLES	(2) Effect on VIX	(3) Effect on VIX
NYchampionship	-2.289	
	(2.225)	
NYChampElimination	-0.835	
	(2.225)	
NYCPlayoffWin		0.693
		(0.428)
NYCPlayoffLoss		-0.143
		(0.437)
Constant	-4.884	-6.366
	(22.10)	(22.12)
Observations	6,231	6,231
R-squared	0.025	0.025
Month Effect	Yes	Yes
Day Effect	Yes	Yes
Year Effect		

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Effect on the difference between the value of the VIX and its 60-day moving average

VARIABLES	(2) Effect on VIX	(3) Effect on VIX
NYchampionship	-1.552	
	(1.506)	
NYChampElimination	0.184	
	(1.506)	
NYCPlayoffWin		-0.037
		(0.289)
NYCPlayoffLoss		-0.184
		(0.297)
Constant	11.37	11.61
	(15.17)	(15.19)
Observations	6,174	6,174
R-squared	0.061	0.061
Month Effect	Yes	Yes
Day Effect	Yes	Yes
Year Effect		

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Effect on Change in the Level of the VIX from the previous trading day

VARIABLES	(2) Effect on VIX	(3) Effect on VIX
NYchampionship	-0.700	
	(0.539)	
NYChampElimination	-0.168	
	(0.539)	
NYCPlayoffWin		0.145
		(0.104)
NYCPlayoffLoss		0.001
		(0.106)
Constant	0.719	0.380
	(5.354)	(5.359)
Observations	6,231	6,231
R-squared	0.016	0.016
Month Effect	Yes	Yes
Day Effect	Yes	Yes
Year Effect		

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Results of Regression on Volume

VARIABLES	(1) Effect on S&P500 Volume	(2) Effect on S&P500 Volume
NYchampionship	-52.11	
	(960.1)	
NYChampElimination	-67.39	
	(960.3)	
NYCPlayoffWin		-26.07
		(184.5)
NYCPlayoffLoss		-12.75
		(189.2)
Constant	2,998	3,062
	(9,603)	(9,613)
Observations	6,208	6,208
R-squared	0.003	0.003
Month Effect	Yes	Yes
Day Effect	Yes	Yes

Year Effect
Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

VARIABLES	(1) Effect on NYSE Volume	(2) Effect on NYSE Volume
NYchampionship	-12.16	
	(14.45)	
NYChampElimination	4.664	
	(24.98)	
NYCPlayoffWin		0.047
		(3.058)
NYCPlayoffLoss		0.649
		(2.714)
Constant	-635.0**	-632.6**
	(289.4)	(289.5)
Observations	2,832	2,832
R-squared	0.042	0.042
Month Effect	Yes	Yes
Day Effect	Yes	Yes

Year Effect
Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

VARIABLES	(1) Effect on DJIA Volume	(2) Effect on DJIA Volume	(3) Effect on DJIA Volume
YankeesPlayoffWin	-3.560		
	(3.866)		
YankeesPlayoffLoss	8.713*		
	(4.618)		
NYchampionship		-4.752	
		(11.19)	
NYChampElimination		-3.186	
		(10.47)	
NYCPlayoffWin			-1.856
			(2.107)
NYCPlayoffLoss			2.053
			(2.188)
Constant	-132.7	-133.6	-128.6
	(127.5)	(126.2)	(126.6)
Observations	5,467	5,468	5,468
R-squared	0.048	0.046	0.046
Month Effect	Yes	Yes	Yes
Day Effect	Yes	Yes	Yes
Year Effect	Yes		

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

VARIABLES	(1) Effect on NASDAQ Volume	(2) Effect on NASDAQ Volume
NYchampionship	-5.255	
	(9.288)	
NYChampElimination	-6.243	
	(9.285)	
NYCPlayoffWin		-1.971
		(1.893)
NYCPlayoffLoss		0.324
		(1.959)
Constant	-75.44	-69.46
	(120.9)	(121.2)
Observations	4,966	4,966
R-squared	0.045	0.045
Month Effect	Yes	Yes
Day Effect	Yes	Yes

Year Effect
Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

VARIABLES	(1) Effect on S&P100 Volume	(2) Effect on S&P100 Volume
NYCPlayoffWin	-2.488	
	(15.62)	
NYCPlayoffLoss	-1.509	
	(16.22)	
NYchampionship		-2.378
		(82.96)
NYChampElimination		-7.036
		(77.62)
Constant	387.2	375.5
	(937.5)	(934.8)
Observations	5,478	5,478
R-squared	0.003	0.003
Month Effect	Yes	Yes
Day Effect	Yes	Yes

Year Effect
Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

	(1)	(2)
VARIABLES	Effect on S&P600 Volume	Effect on S&P600 Volume
NYCPlayoffWin	-0.004	
	(0.502)	
NYCPlayoffLoss	0.021	
	(0.520)	
NYchampionship		0.079
		(2.464)
NYChampElimination		-0.201
		(2.463)
Constant	15.85	15.89
	(32.20)	(32.14)
Observations	4,960	4,960
R-squared	0.003	0.003
Month Effect	Yes	Yes
Day Effect	Yes	Yes

Year Effect
Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Event Study Approach Results

Dow Jones

Event	Event Window	CAR	T-Stat	P-Value
NYC Championship (n=31)	(0,1)	-0.079%	-0.421	0.661
	(0,2)	0.005%	0.034	0.486
	(0,5)	-0.008%	-0.114	0.545
	(0,10)	-0.011%	-0.176	0.569
	(0,20)	0.042%	1.052	0.150
	(0,30)	0.044%	1.207	0.118
NYC Championship Loss (n=27)	(0,1)	0.250%	1.233	0.885
	(0,2)	0.299%	2.066	0.975
	(0,5)	0.081%	0.977	0.831
	(0,10)	0.013%	0.247	0.596
	(0,20)	-0.043%	-1.112	0.138
	(0,30)	-0.034%	-0.796	0.216

NYSE

Event	Event Window	CAR	T-Stat	P-Value
NYC Championship (n=22)	(0,1)	-0.100%	-0.387	0.649
	(0,2)	0.063%	0.316	0.377
	(0,5)	0.026%	0.271	0.271
	(0,10)	0.030%	0.354	0.363
	(0,20)	**0.062%**	**1.366**	**0.093**
	(0,30)	**0.059%**	**1.335**	**0.098**
NYC Championship Loss (n=14)	(0,1)	0.427%	1.344	0.899
	(0,2)	0.571%	2.488	0.986
	(0,5)	0.191%	1.577	0.930
	(0,10)	0.049%	0.645	0.734
	(0,20)	-0.046%	-0.815	0.214
	(0,30)	-0.043%	-0.687	0.251

S&P500

Event	Event Window	CAR	T-Stat	P-Value
NYC Championship (n=22)	(0,1)	-0.093%	-0.388	0.649
	(0,2)	0.080%	0.420	0.339
	(0,5)	0.052%	0.570	0.287
	(0,10)	0.038%	0.467	0.322
	(0,20)	**0.068%**	**1.504**	**0.073**
	(0,30)	**0.066%**	**1.508**	**0.073**
NYC Championship Loss (n=15)	(0,1)	0.427%	1.470	0.918
	(0,2)	0.576%	2.685	0.991
	(0,5)	0.200%	1.733	0.947
	(0,10)	0.030%	0.400	0.652
	(0,20)	-0.050%	-0.997	0.167
	(0,30)	-0.037%	-0.625	0.270

Nasdaq

Event	Event Window	CAR	T-Stat	P-Value
NYC Championship (n=19)	(0,1)	-0.344%	-1.081	0.853
	(0,2)	0.060%	0.242	0.405
	(0,5)	0.094%	0.581	0.284
	(0,10)	0.040%	0.302	0.382
	(0,20)	0.049%	0.528	0.301
	(0,30)	0.061%	0.678	0.253
NYC Championship Loss (n=14)	(0,1)	0.097%	0.238	0.592
	(0,2)	0.498%	1.911	0.960
	(0,5)	0.143%	0.785	0.776
	(0,10)	-0.037%	-0.258	0.400
	(0,20)	-0.103%	-1.095	0.146
	(0,30)	-0.091%	-0.825	0.212

S&P 100

Event	Event Window	CAR	T-Stat	P-Value
NYC Championship	(0,1)	-0.363%	-1.467	0.919
(n=17)	(0,2)	-0.125%	-0.827	0.790
	(0,5)	-0.116%	-1.181	0.872
	(0,10)	-0.091%	-1.196	0.875
	(0,20)	-0.085%	-1.604	0.935
	(0,30)	-0.080%	-1.514	0.925
NYC Championship Loss	**(0,1)**	**-0.822%**	**-2.031**	**0.034**
(n=11)	(0,2)	-0.376%	-1.351	0.103
	(0,5)	-0.041%	-0.276	0.393
	(0,10)	0.105%	1.330	0.893
	(0,20)	0.092%	1.111	0.853
	(0,30)	0.106%	1.247	0.879

S&P 600

Event	Event Window	CAR	T-Stat	P-Value
NYC Championship	(0,1)	-1.049%	-1.541	0.912
(n=7)	(0,2)	-0.493%	-2.335	0.970
	(0,5)	-0.310%	-2.030	0.955
	(0,10)	-0.217%	-1.411	0.896
	(0,20)	-0.099%	-0.940	0.808
	(0,30)	-0.093%	-0.875	0.792
NYC Championship Loss	**(0,1)**	**-1.148%**	**-1.949**	**0.046**
(n=8)	**(0,2)**	**-0.391%**	**-1.431**	**0.097**
	(0,5)	-0.186%	-1.171	0.139
	(0,10)	-0.067%	-1.013	0.172
	(0,20)	0.038%	0.344	0.629
	(0,30)	0.045%	0.426	0.658

VIX

Event	Event Window	Mean	T-Stat	P-Value (Two Sided)
NYC Championship	(0,1)	-0.639	-0.313	0.763
(n=8)	(0,2)	-0.841	-0.411	0.693
	(0,5)	-0.937	-0.489	0.639
	(0,10)	-1.388	-0.792	0.454
	(0,20)	-1.989	-1.126	0.297
	(0,30)	-2.050	-1.169	0.280
NYC Championship Loss	(0,1)	0.184	0.127	0.901
(n=8)	(0,2)	-0.228	-0.162	0.875
	(0,5)	-0.572	-0.392	0.706
	(0,10)	-0.639	-0.421	0.686
	(0,20)	-0.438	-0.271	0.793
	(0,30)	-0.399	-0.248	0.810

DJIA VOLUME

Event	Event Window	Mean	T-Stat	P-Value (Two Sided)	P-Value (>0)
NYC Championship	(0,1)	1.50E+07	0.644	0.542	0.271
(n=7)	(0,2)	1.34E+07	0.732	0.491	0.245
	(0,5)	4193784	0.277	0.791	0.395
	(0,10)	1.94E+06	0.152	0.883	0.441
	(0,20)	248447.4	0.023	0.982	0.491
	(0,30)	884498.8	0.083	0.936	0.468
NYC Championship Loss	**(0,1)**	**2.41E+07**	**2.350**	**0.051**	**0.025**
(n=8)	**(0,2)**	**2.55E+07**	**2.773**	**0.027**	**0.013**
	(0,5)	1.04E+07	1.240	0.254	0.872
	(0,10)	1.01E+07	0.762	0.470	0.235
	(0,20)	5407079	0.461	0.658	0.329
	(0,30)	6422504	0.559	0.593	0.296

S&P500 VOLUME

Event	Event Window	Mean	T-Stat	P-Value (Two Sided)	P-Value (>0)
NYC Championship (n=8)	(0,1)	6.08E+07	0.755	0.474	0.237
	(0,2)	6.23E+07	0.886	0.404	0.202
	(0,5)	5.02E+07	0.748	0.478	0.239
	(0,10)	3.45E+07	0.629	0.548	0.274
	(0,20)	1.27E+07	0.267	0.796	0.398
	(0,30)	1.36E+07	0.286	0.783	0.391
NYC Championship Loss (n=8)	**(0,1)**	**1.34E+08**	**2.368**	**0.049**	**0.024**
	(0,2)	**1.51E+08**	**2.854**	**0.024**	**0.012**
	(0,5)	8.83E+07	1.846	0.107	0.053
	(0,10)	8.18E+07	1.635	0.146	0.073
	(0,20)	4.78E+07	1.066	0.321	0.160
	(0,30)	5.64E+07	1.203	0.268	0.134

S&P 600 Volume

Event	Event Window	Mean	T-Stat	P-Value (Two Sided)	P-Value (>0)
NYC Championship (n=7)	(0,1)	1.11E+07	1.144	0.296	0.148
	(0,2)	8330877	1.334	0.230	0.115
	(0,5)	6681262	1.317	0.235	0.117
	(0,10)	4495571	0.934	0.386	0.193
	(0,20)	1883272	0.439	0.675	0.337
	(0,30)	1528881	0.358	0.732	0.366
NYC Championship Loss (n=7)	**(0,1)**	**2.27E+07**	**2.379**	**0.054**	**0.027**
	(0,2)	**1.47E+07**	**2.401**	**0.053**	**0.026**
	(0,5)	6708491	1.395	0.212	0.106
	(0,10)	**4554942**	**1.453**	0.196	**0.098**
	(0,20)	1397173	0.383	0.714	0.357
	(0,30)	2235518	0.637	0.547	0.273

S&P 100 Volume

Event	Event Window	Mean	T-Stat	P-Value (Two Sided)	P-Value (>0)
NYC Championship (n=7)	(0,1)	3.94E+07	0.745	0.484	0.242
	(0,2)	3.73E+07	0.846	0.429	0.214
	(0,5)	1.98E+07	0.510	0.628	0.314
	(0,10)	1.26E+07	0.394	0.707	0.353
	(0,20)	2440890	0.088	0.932	0.533
	(0,30)	3321461	0.120	0.907	0.453
NYC Championship Loss (n=8)	**(0,1)**	**7.08E+07**	**2.344**	**0.051**	**0.025**
	(0,2)	**7.75E+07**	**3.020**	**0.019**	**0.009**
	(0,5)	**4.17E+07**	**2.005**	**0.085**	**0.042**
	(0,10)	4.37E+07	1.696	0.133	**0.066**
	(0,20)	2.95E+07	1.261	0.247	0.123
	(0,30)	3.23E+07	1.378	0.210	0.105

Falsification Test for Event Study performed on Los Angeles sports outcomes

NYSE

Event	Event Window	CAR	T-Stat	P-Value
LA Championship	(0,1)	-0.176	-0.913	0.811
(n=14)	(0,2)	-0.166	-1.046	0.842
	(0,5)	-0.122	-1.072	0.848
	(0,10)	-0.079	-0.98	0.827
	(0,20)	-0.052	-0.87	0.8
	(0,30)	-0.033	-0.572	0.711
LA Championship Loss	(0,1)	0.095	0.418	0.659
(n=13)	(0,2)	0.112	0.556	0.706
	(0,5)	0.004	0.035	0.514
	(0,10)	-0.011	-0.116	0.454
	(0,20)	0.007	0.12	0.546
	(0,30)	0.019	0.332	0.627

S&P500

Event	Event Window	CAR	T-Stat	P-Value
LA Championship	(0,1)	-0.105	-0.546	0.703
(n=15)	(0,2)	-0.104	-0.664	0.741
	(0,5)	-0.084	-0.754	0.768
	(0,10)	-0.061	-0.748	0.767
	(0,20)	-0.035	-0.631	0.731
	(0,30)	-0.025	-0.454	0.672
LA Championship Loss	(0,1)	0.115	0.505	0.689
(n=14)	(0,2)	0.111	0.583	0.715
	(0,5)	0.004	0.034	0.513
	(0,10)	-0.009	-0.103	0.460
	(0,20)	-0.006	-0.116	0.455
	(0,30)	0.005	0.096	0.538

S&P 100

Event	Event Window	CAR	T-Stat	P-Value
LA Championship	(0,1)	0.161	0.559	0.293
(n=13)	(0,2)	0.224	0.956	0.179
	(0,5)	0.017	0.123	0.452
	(0,10)	0.085	0.935	0.184
	(0,20)	0.011	0.158	0.439
	(0,30)	-0.014	-0.233	0.590
LA Championship Loss	(0,1)	0.050	0.121	0.546
(n=8)	(0,2)	-0.036	-0.169	0.435
	(0,5)	0.071	0.429	0.660
	(0,10)	0.048	0.499	0.317
	(0,20)	0.016	0.366	0.637
	(0,30)	0.037	1.017	0.829

S&P 600

Event	Event Window	CAR	T-Stat	P-Value
LA Championship	(0,1)	0.164	0.267	0.400
(n=6)	(0,2)	0.171	0.396	0.354
	(0,5)	-0.078	-0.339	0.626
	(0,10)	0.054	0.262	0.402
	(0,20)	-0.061	-0.551	0.697
	(0,30)	-0.088	-0.738	0.753
LA Championship Loss	(0,1)	0.857	1.826	0.841
(n=2)	(0,2)	0.599	1.130	0.769
	(0,5)	0.366	0.601	0.672
	(0,10)	0.396	0.686	0.691
	(0,20)	0.205	2.446	0.877
	(0,30)	0.187	3.142	0.902

DJIA VOLUME

Event	Event Window	Mean	T-Stat	P-Value (Two Sided)	P-Value (<0)
LA Championship	(0,1)	-2.57E+07	-1.278	0.257	0.129
(n=6)	**(0,2)**	**-3.10E+07**	**-1.664**	**0.157**	**0.079**
	(0,5)	-1.00E+07	-0.979	0.373	0.186
	(0,10)	-1.60E+07	-1.046	0.344	0.172
	(0,20)	-2.61E+07	-1.468	0.202	0.101
	(0,30)	**-2.59E+07**	**-1.500**	**0.194**	**0.097**
LA Championship Loss	**(0,1)**	**-2.13E+07**	**-1.939**	**0.192**	**0.096**
(n=3)	(0,2)	3.12E+07	1.663	0.238	0.881
	(0,5)	966349	0.144	0.899	0.551
	(0,10)	1.06E+07	1.614	0.248	0.876
	(0,20)	1596668	0.575	0.623	0.688
	(0,30)	4256901	1.559	0.259	0.870

S&P500 VOLUME

Event	Event Window	Mean	T-Stat	P-Value (Two Sided)	P-Value (<0)
LA Championship	**(0,1)**	**-1.14E+08**	**-2.082**	**0.092**	**0.046**
(n=6)	**(0,2)**	**-1.03E+08**	**-2.389**	**0.062**	**0.031**
	(0,5)	-2.15E+07	-0.837	0.441	0.220
	(0,10)	-4.68E+07	-1.410	0.218	0.109
	(0,20)	**-8.55E+07**	**-1.995**	**0.103**	**0.051**
	(0,30)	**-8.21E+07**	**-2.032**	**0.098**	**0.049**
LA Championship Loss	**(0,1)**	**-8.21E+07**	**-1.874**	**0.158**	**0.079**
(n=4)	**(0,2)**	2.65E+07	0.555	0.617	0.691
	(0,5)	**-3.55E+07**	**-3.176**	**0.050**	**0.025**
	(0,10)	**-4653412**	**-0.415**	**0.706**	**0.353**
	(0,20)	-1.01E+07	-0.445	0.686	0.343
	(0,30)	-5517412	-0.224	0.837	0.419

S&P100 VOLUME

Event	Event Window	Mean	T-Stat	P-Value (Two Sided)	P-Value (<0)
LA Championship (n=6)	(0,1)	-4.36E+07	-1.305	0.249	0.124
	(0,2)	**-5.25E+07**	**-2.248**	**0.075**	**0.037**
	(0,5)	-1.39E+07	-0.991	0.367	0.184
	(0,10)	-2.79E+07	-1.341	0.238	0.119
	(0,20)	**-5.17E+07**	**-2.123**	**0.087**	**0.044**
	(0,30)	**-5.02E+07**	**-2.144**	**0.085**	**0.042**
LA Championship Loss (n=3)	**(0,1)**	**-5.92E+07**	**-2.355**	**0.143**	**0.071**
	(0,2)	3.10E+07	1.053	0.403	0.799
	(0,5)	**-1.97E+07**	**-2.008**	**0.182**	**0.091**
	(0,10)	-2258511	-1.687	0.234	0.117
	(0,20)	-1.36E+07	-1.731	0.226	0.113
	(0,30)	-9706324	-1.241	0.341	0.170

S&P600 VOLUME

Event	Event Window	Mean	T-Stat	P-Value (Two Sided)	P-Value (>0)
LA Championship (n=6)	(0,1)	-1347156	-0.209	0.843	0.579
	(0,2)	-1309880	-0.217	0.837	0.582
	(0,5)	6442214	1.371	0.229	0.114
	(0,10)	**6551009**	**2.693**	**0.043**	**0.022**
	(0,20)	242878.6	0.080	0.939	0.470
	(0,30)	199182	0.068	0.949	0.474
LA Championship Loss (n=2)	(0,1)	751340	0.029	0.982	0.491
	(0,2)	**3.97E+07**	**5.158**	**0.122**	**0.061**
	(0,5)	**7809763**	**7.687**	**0.082**	**0.041**
	(0,10)	**2.26E+07**	**8.059**	**0.079**	**0.039**
	(0,20)	9145739	2.895	0.212	0.106
	(0,30)	8771668	2.918	0.210	0.105