# Local Sports Sentiment and the Returns and Trading Behavior of Locally Headquartered Stocks: A Firm-Level Analysis


## Abstract

We undertake firm-level analysis of the relation between National Football League (NFL) game outcomes and the return patterns and trading behavior of Nasdaq firms headquartered in the same geographic areas as the NFL teams. We find that losses by local teams lead to lower next-day returns for locally headquartered stocks, especially when losses are in succession and investors are more bearish. The negative effects of game losses are stronger for stocks that are more vulnerable to shifts in sports sentiment. Game losses influence next-day returns negatively only at the market open, however. Consistent with this finding, game losses are associated with more seller-initiated trades and reduced market depth at the market open. Game losses also lead to lower trading volume during the opening period, especially for individual traders, who are most likely to be influenced by sports sentiment.

# Local Sports Sentiment and the Returns and Trading Behavior of Locally Headquartered Stocks: A Firm-Level Analysis

## I. Introduction

A growing body of literature investigates the effect of investor sentiment on asset prices. This literature argues that psychological factors influence stock returns. The mood of investors tends to affect their evaluations of future prospects and hence their trading behavior in financial markets. The variables seen to affect investor mood are related primarily to weather conditions, including sunshine (Saunders, 1993; Hirshleifer and Shumway, 2003; Chang et al., 2008), daylight (Kamstra et al., 2000, 2003), temperature (Cao and Wei, 2005), and lunar cycles (Yuan et al., 2006). Most recently, Edmans et al. (2007) argue that the outcomes of sporting events also have a significant effect on stock returns, following the ample psychological evidence that sports results affect investors' moods and assessments of themselves and life in general (Schwarz et al., 1987; Wann et al., 1994; Bizman and Yinon, 2002; Ashton et al., 2003). Edmans et al. (2007) find that losses in soccer, cricket, rugby, and basketball in a cross-section of 39 countries have a negative impact on the losing country's stock market index.

We extend Edmans et al. (2007) by investigating the potential effects of sports sentiment on stock returns and trading activities at the firm level. We examine the relation between American football game outcomes and the return patterns and trading behavior of Nasdaq firms headquartered in the same geographic areas as the cities of National Football League (NFL) teams. Our research makes several valuable contributions to the literature. First, unlike Edmans et al. (2007), who analyze the effects of sports results using aggregate stock market indices, we undertake firm-level analysis to study these effects. Baker and Wurgler (2006) suggest that investor sentiment has a heterogeneous impact on stock returns across firms with different characteristics. Small companies, young companies, high-growth companies, non-dividend-paying companies, and companies with high return volatility, low asset tangibility, and low asset profitability are more likely to be affected by shifts in investor sentiment. The firm-level data we use allow us to examine how sports outcomes affect investor mood for such stocks.

Second, we examine the effects of sports sentiment on both daily and intraday stock returns, in contrast to Edmans et al. (2007), who base their findings on daily returns. Harris (1986), Atkins and Dyl (1990), Stoll and Whaley (1990), and Fabozzi et al. (1995) all document a strong seasonality in intraday return patterns. Our intraday analysis provides a finer picture that cannot be readily seen in daily observations. This advantage is particularly valuable if sports sentiment affects stock returns more significantly at certain trading hours, say, at market opening periods, and we cannot capture those effects by examining daily data. Our intraday analysis also permits a more reliable and efficient estimation of the effect of sports sentiment on share prices, because the short measurement period mitigates the sources of variability that may be attributed to some unrelated extraneous factors (Barclay and Litzenberger, 1988; Busse and Green, 2002). This advantage is particularly important in the case of interpretation of the effect of sports sentiment on stock markets, given that the correlation between mood-related variables and stock returns may be driven by outliers and subsamples (Pinegar, 2002).

Third, we provide additional general evidence on the effects of sports sentiment on investor trading activities. Brown (1999), Baker and Stein (2004), and Chang et al.

(2008) show that investor sentiment is correlated with trading variables such as trading volume, bid-ask spread, quoted depth, and order imbalance. If sports outcomes affect investor sentiment, it is likely that sports outcomes will also have important effects on their trading behavior. Cohen et al. (2002) and Loughran and Schultz (2004) suggest that individual investors are less likely to value securities rationally than institutional investors. Thus one would expect sports sentiment to have a more pronounced effect on the trading activities of individual investors than institutional investors.

Finally, one potential limitation in Edmans et al. (2007), as they relate country stock index returns to sports outcomes that are specific to individual country, is that orders submitted to stock markets may come from investors located all over the world. International investors may set prices at the margin, but they are not affected by particular sports results at all. We take a different approach by examining the relation between local sports results and the return patterns of locally headquartered Nasdaq stocks. Coval and Moskowitz (1999), Grinblatt and Keloharju (2001), Huberman (2001), Zhu (2002), Loughran and Schultz (2004), and Ivkovic and Weisbenner (2005) document that investors disproportionately trade the stocks of firms located nearby.[1] They show that investors who live in the same city as a company's headquarters are more likely to own or buy the stock than investors living elsewhere. This is particularly true of Nasdaq firms, because investors in Nasdaq exhibit a strong pattern of localized trading. Loughran and Schultz (2004) show that a substantial amount of trading for Nasdaq stocks originates

[1] Loughran and Schultz (2004) argue that local stocks are more familiar to local investors. Informal sources of information about local companies, such as conversations with employees and customers, are available to many potential traders and investors. Similarly, local news coverage of local companies reaches many investors in those areas.

from the city where a firm is based, and we believe our study provides a better way to examine the effects of sports-induced moods on stock prices.

We choose American football as the sport for analysis because it is an important part of many Americans' lives and likely to affect the mood of local investors. Neal Pilson, former president of CBS Sports, argues that the football game in some ways sums up the American experience, and a lot of people see the game as linked to the personality and attitude of the country.[2] For more than four decades, according to a Harris Poll, professional football has been the most popular sport in the U.S. In 2008, professional football was the favorite sport of nearly as many people (30%) as the combined total of the next four professional sports—baseball (15%), auto racing (10%), hockey (5%), and men's basketball (4%).[3] Edmans et al. (2007) point out that American football is predominantly contested on a club rather than country level, and football games are likely to influence local investors' moods.

We first examine the impact of NFL game outcomes on the next-day returns of a team's locally headquartered stocks. Locally headquartered stocks with losing teams experience significantly lower next-day returns than stocks with winning teams. Our results are consistent with those in Edmans et al. (2007), supporting the view that the moods of local investors induced by sports effects have a significant impact on the returns of localized trading stocks.

We then show that the negative effects of football game losses on stock returns are stronger when the football teams experience a run of losing games. Investors feel worse

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[2] See *The Washington Post* (Sep. 8, 2005).

[3] See the Harris Interactive website (www.harrisinteractive.com/harris_poll/index.asp?PID=866).

when their teams lose several games in a row, resulting in lower stock returns. The findings support the argument in the literature that a stream of losses in sports tends to generate more bearish sentiments among investors (Gilovich et al., 1985; Camerer, 1989; Tassoni, 1996; Offerman and Sonnemans, 2004).

We find that the impacts of game results on next-day returns of locally headquartered stocks depend on firm characteristics. The negative effects of game losses are found to be significantly stronger for smaller firms, younger firms, non-dividend-paying firms, and firms with higher return volatility and less asset tangibility and profitability. These firms are more likely to be affected by sports results because investor sentiment drives the relative demand for speculative investments, and such stocks are more vulnerable to shifts in the propensity to speculate (Baker and Wurgler, 2006). These shares also tend to be riskier and more costly to trade and to sell short, so they are more difficult to arbitrage, and suffer from highly subjective valuations (Amihud and Mendelson, 1986; D'Avolio, 2002; Duffie et al., 2002; Geczy et al., 2002; Jones and Lamont, 2002; Mitchell et al., 2002; Wurgler and Zhuravskaya, 2002; Lamont and Thaler, 2003). Returns of such stocks are more likely to be affected by sports sentiment.

Examination of the effects of outcomes on intraday returns following game days indicates that football game losses have a significant influence on next-day stock returns only at the market open. The effects become insignificant for subsequent trading intervals. This evidence supports the argument suggested in the literature that investors experiencing significant psychological changes upon a game result act on their moods in the opening trades, but the mood is transient and becomes less important as more information comes to the market during the trading day (Lo and Repin, 2002; Chang et al., 2008). As in the results for daily returns, we find that the negative effects of game losses on stock returns at market opening periods are stronger when football teams experience a run of losses. These effects during the opening trading interval are also found to be stronger for firms that are more vulnerable to shifts in investor sentiment.

Since stock price changes are caused by investors' trading activities, we further investigate how football game outcomes affect trading variables during the opening period of the next trading day. We find that when teams lose games, there are significantly more seller-initiated trades and lower turnover ratios and market depth for the locally headquartered stocks. The evidence supports the hypothesis that investors who are in a down mood due to game losses are more pessimistic, have less desire to trade, and tend to sell rather than buy shares (Loughran and Schultz, 2004; Goetzmann and Zhu, 2005; Chang et al., 2008). We also find significantly stronger negative effects of game losses on trading volume around the market open for individual traders than institutional traders. This finding is consistent with the argument suggested in the literature that the impact of sports-induced sentiment is stronger for non-institutional investors (Cohen et al., 2002; Loughran and Schultz, 2004). Non-institutional investors are more likely to be influenced by sports results, and they trade less when they are in a bad mood caused by game losses.

We finally examine whether football game results affect the next-day returns of firms listed on the New York Stock Exchange (NYSE) where orders come from all over the world (Bessembinder, 2003; Bacidore et al., 2005). We focus on the impact of game outcomes on NYSE firms headquartered in the same geographic areas as the cities of

NFL teams. In this case, we find no significant impact of game outcomes on the returns of NYSE stocks both during the opening trading interval and throughout the day. This finding supports the argument by Loughran and Schultz (2004) that trading in Nasdaq stocks is more localized. Hence local football game results have a more pronounced impact on Nasdaq stocks than on NYSE stocks.

The remainder of the paper proceeds as follows. Section II develops our hypotheses. Section III describes the sample and presents summary statistics. In Section IV, we examine the impact of football game outcomes on the returns of Nasdaq stocks and explore the role of firm characteristics in explaining this impact. In Section V, we focus on the intraday patterns of stock returns and trading activity. Section VI examines the impact of sports sentiment on the returns of NYSE stocks. The final section concludes the paper.

## II. Hypothesis Development

We first develop hypotheses on the relation between football game outcomes and stock returns. We further explore how firm characteristics affect this relation. We then discuss the potential effects of game outcomes on intraday patterns of stock returns. Finally, we develop several hypotheses on how game outcomes may affect investors' trading activities.

### *A. Sports Sentiment and Daily Stock Returns*

Considerable psychological evidence demonstrates that sports results have a significant influence on mood (Schwarz et al., 1987; Arkes et al., 1988; Hirt et al., 1992; Schweitzer et al., 1992; Wann et al., 1994; Wann and Branscombe, 1995; Bizman and

Yinon, 2002; Ashton et al., 2003). Fans show a negative or positive reaction depending on their team performance. They often have strong negative reactions when their team loses and strong positive reactions when their team wins. These reactions make fans pessimistic or optimistic on life in general (Edmans et al., 2007). If sports results affect people's evaluations of future prospects, they also influence investors' trading behavior in financial markets, resulting in stock price changes. Therefore, when a football team loses, local investors will be in a poorer mood and tend to be more pessimistic as to future prospects. This suggests that losses in football games by local teams lead to lower returns for locally headquartered stocks. The converse arguments apply to wins. We formulate our first hypothesis as follows:

***Hypothesis 1***. Locally headquartered companies where there are losing football teams experience lower returns than companies where there are winning football teams.

The effects of game losses on returns may depend on the past record of a team. Previous results suggest that a stream of losses in sports tends to generate more bearish sentiments in investors. Gilovich et al. (1985) identify a systematic bias in people's beliefs in the case of predicting future sports events. They suggest that both sports players and fans believe players are more likely to perform poorly if past performance has been unsuccessful. Fans and bettors tend to see trends in a team's past record and overestimate the autocorrelation in the results of a string of games. Camerer (1989) examines whether there are beliefs in autocorrelation in the betting market for basketball teams. Like Gilovich et al. (1985), he finds that losing teams are undervalued by bettors on National Basketball Association games. Tassoni (1996) documents similar findings for NFL football games. Offerman and Sonnemans (2004) apply an experimental design to demonstrate that traders tend to discover trends in the past record of a team and overestimate autocorrelation in the series. In addition, the more bearish sentiment resulting from a stream of game losses may be caused by the psychological phenomenon of recency. Kahneman and Tversky (1982) suggest that people tend to overweight recent experience more than long-term averages when they process information. Thus fans of local football teams may become more pessimistic as their teams experience recent successive losses. De Bondt and Thaler (1985, 1987) provide evidence supporting the recency bias in financial markets. The second hypothesis is:

***Hypothesis 2***. The lower return effects of football game losses for locally headquartered stocks are stronger when the local teams experience a run of losses.

The effects of game outcomes on stock returns may also depend on firm characteristics. Baker and Wurgler (2006) document that small companies, young companies, high-growth companies, non-dividend-paying companies, and companies with high return volatility, low asset tangibility, and low asset profitability are more likely to be affected by shifts in investor sentiment. They argue that investor sentiment drives the relative demand for speculative investments and that these stocks are more vulnerable to shifts in the propensity to speculate. Arbitrage tends to be risky and costly for these stocks. They have high idiosyncratic risk and low liquidity, and are more costly to trade or sell short (Amihud and Mendelson, 1986; D'Avolio, 2002; Duffie et al., 2002; Geczy et al., 2002; Jones and Lamont, 2002; Mitchell et al., 2002; Wurgler and Zhuravskaya, 2002; Lamont and Thaler, 2003; Brunnermeier and Pedersen, 2005). The stocks that are hardest to arbitrage also tend to be the most difficult to value, so the valuations of firms with the characteristics identified by Baker and Wurgler (2006) are highly subjective, and their trading is more likely to be affected by investor sentiment. We thus have the third hypothesis:

***Hypothesis 3***. The negative effects of football game losses on the returns of locally headquartered stocks are stronger for small firms, young firms, high-growth firms, non-dividend-paying firms, and firms with high return volatility, low asset profitability, and low asset tangibility.

*B. Sports Sentiment and Intraday Patterns in Stock Returns*

Researchers document significant intraday return patterns (Harris, 1986; Atkins and Dyl, 1990; Stoll and Whaley, 1990; Fabozzi et al., 1995). It is thus possible that football game results may affect stock returns more significantly at certain intraday trading intervals. Moods induced by sports outcomes could have a more pronounced influence on investors' decision-making process at the start of trading. This is because investors observing the game outcomes of the previous day and experiencing psychological changes act on their moods in the opening trades (Lo and Repin, 2002; Chang et al., 2008). Nevertheless, as more information comes to the market during the trading day, the impact of sports results on stock returns diminishes quickly. We hence formulate the fourth hypothesis as follows:

***Hypothesis 4***. The effects of football game outcomes on the returns of locally headquartered stocks are stronger at the market open but will not last for the entire trading day.

*C. Sports Sentiment and Trading Behavior*

If sports results affect the mood and sentiment of investors, it seems likely that sports sentiment will have important effects on their trading behavior as well. Baker and Stein (2004) argue that when investor sentiments are bullish, investors may become overconfident, and consider others to be not as well-informed. With overconfidence, investors overestimate the relative precision of their own private signals and underestimate the information content embodied in either order flow or equity issues and others' trading decisions. A market whose pricing is dominated by bullish sentiment levels is therefore unusually liquid. A highly liquid market is usually characterized by high depth and trading volume and narrow bid-ask spreads. Loughran and Schultz (2004), Goetzmann and Zhu (2005), and Chang et al. (2008) argue that when investors are in a bad mood, they become more pessimistic and have less of a desire to trade and tend to sell rather than buy. These studies suggest that investor sentiment is positively related to the turnover ratio, market depth, and number of buy orders and negatively related to the bid-ask spread. Therefore, if sports results affect investor sentiment, we have the hypothesis:

***Hypothesis 5***. Locally headquartered companies where there are losing football teams experience lower stock turnover ratios, market depth, and numbers of buy orders, but higher bid-ask spreads, relative to companies where there are winning football teams.

Our final hypothesis deals with how investor types affect the relation between sports sentiment and trading volume. Cohen et al. (2002) and Loughran and Schultz (2004) suggest that individual investors are more likely to deviate from rational valuation of securities than are institutional investors. Kaniel et al. (2008) and Keswani and Stolin (2008) point out that individuals and institutions tend to exhibit different investment behaviors. While institutions are likely to be better informed and apply more sophisticated investment techniques, individuals tend to have psychological biases and are often either the liquidity or noise traders in the sense of Kyle (1985) or Black (1986). All these studies suggest that sports sentiment has a stronger effect on individual investors than on institutional investors. We have hypothesized that investors in a down mood become more pessimistic and less inclined to trade. The sports-induced impact is expected to be more pronounced for individual investors.

***Hypothesis 6***. Football game losses on the trading volume of locally headquartered stocks have significantly stronger negative effects for non-institutional traders than for institutional traders.

## III. Sample and Descriptive Statistics

To examine the relation between local sports results and the return patterns and trading behavior of locally headquartered stocks, we confine our attention to Nasdaq stocks because their returns are particularly affected by the mood of local investors (Loughran and Schultz, 2004). We use the first three digits of the zip code to determine whether the headquarter of a Nasdaq firm is located in the same geographic area as the city of a National Football League team.[4] We first obtain the data from the official NFL

[4] The first three digits of the zip code generally represent a metropolitan city, or a cluster of suburban cities surrounding a metropolis. It is indicated on the United States Postal Service website that the first three digits of the zip code represent a sectional center or a large city. Previous studies have used the first three digits of the zip code as the metropolitan boundary (Lin and Alexander, 2004; Johnson et al., 2006; Eff and Livingston, 2007).

website (www.nfl.com) for the city where a football team is located. We then use the website of the United States Postal Service (www.usps.com) to identify the zip code of the city of the football team. We also obtain the zip codes of firm headquarters from the Compustat database. If a Nasdaq firm's headquarter and the city of an NFL football team have the same first three-digit zip code, they are defined as in the same geographic area. Therefore, our sample firms are the Nasdaq firms located in same geographic areas as the cities of NFL football teams.[5]

We require the firms in our sample to be covered by the University of Chicago's Center for Research in Stock Prices (CRSP) database and the Compustat database. The sample period runs from September 1994 through December 2004. CRSP provides the daily return, price, and shares outstanding information, and Compustat provides firms' financial information for the sample. We obtain intraday returns and trading data (such as trade prices, bid-ask quotes, trading volume, and quote size) from the Trade and Quote (TAQ) database. To minimize trading data errors, we follow Chordia et al. (2002) and apply several filters. If a trade is out of sequence or has special settlement conditions, we exclude it, because it might then have been affected by distinctive liquidity considerations. We also exclude quotes recorded outside the regular trading hours (9:30-16:00) and observations with negative bid-ask spreads.[6]

We collect the NFL game results from Statfox (www.statfox.com/default.htm), a premier sports handicapping community on the Internet that provides game statistics and betting information for all the major sports in the U.S. and Canada. The NFL had 28

[5] No NFL football teams have the same first three-digit zip codes.

[6] To acknowledge the non-synchronous trading problem for illiquid stocks, we repeat all tests in the study by excluding 10% of the least liquid Nasdaq firms that are located in the same geographic area as the city of each football team. Findings are similar in this case too.

teams in 1994 and then expanded to 30 teams in 1995, 31 teams in 1999, and 32 teams in 2002. Each team plays 16 games in a regular season, starting in early September and ending in late December or early January of the next year. The majority of the games take place on Sunday afternoon, although some are played at other times (generally Monday, Thursday, or Sunday nights). To measure the impact of football game results, we use stock returns and trading variables on the first trading day following the game. Since football games occur after the stock market closes, the use of the first trading day after the game ensures that we have the return patterns and trading measures for the full day when the game outcome is known.

To measure the stock market impact of marginal sentiment induced by football games, we must first adjust for pre-game expectations. Betting point-spread is a common measure of market expectations about results for a variety of sports in the U.S., including football (Zuber et al., 1985; Gandar et al., 1988; Gray and Gray, 1997; Avery and Chevalier, 1999), basketball (Brown and Sauer, 1993), and baseball (Woodland and Woodland, 1994). Information on the betting market is widely assimilated and quickly updated in sports-related websites, newsletters, sports shows, newspaper columns, and so on (Avery and Chevalier, 1999). There are many professional bettors in the sports point-spread market who attempt to exploit any potential mispricing opportunity. Thus, the betting lines reflect pre-game expectations and sentiments.

Adjustment for pre-game expectations is important because a game may result in strong disappointment when a team expected to win by a wide margin just barely beats its opponent. Previous studies have shown that the performance difference of the competing teams has a strong effect on the sentiment-related variables. Welki and

Zlatoper (1999) find that the pre-game point spreads significantly affect the attendance of NFL games. Fisher and Wakefield (1998) show that the perceived relative team performance is the most important factor leading to identification for members of successful groups. Edmans et al. (2007) also recognize the importance of controlling for disparity in skill among participating countries, when studying the impact of sports sentiment from international soccer games. They choose games with teams that are close in ability, which in effect controls for pre-game expectations. This is similar to our approach of making adjustments based on the betting point spreads.[7]

We use the betting point spreads provided by Statfox, and define a football team as losing a game if it fails to cover the point spread and winning if it covers the point spread. For example, if the betting line indicates that Pittsburgh is favored over Dallas by 5 points, Pittsburgh wins the game when it beats Dallas by more than 5 points; it loses if it wins by less than 5 points. The game is considered tied when Pittsburgh beats Dallas by exactly 5 points. We use the closing betting spread for adjustment, as Avery and Chevalier (1999) find that more new information and pre-game sentiment are incorporated into the closing line than the opening line. Gandar et al. (1988) also show that the closing point spread has a stronger predictive power on the actual game spread than does the opening point spread.

Table I presents sample distributions by year and summary statistics. Panel A shows that the number of Nasdaq firms in our sample increases steadily in the 1990s and then fluctuates around 10,500 in the 2000s. Panel B presents summary statistics for

[7] It is likely that many fans, except the gamblers, do not know that their local football teams are favored. If their teams lose, their fans will be disappointed regardless of whether or not the teams lose by more than the spread. We repeat all the tests without adjusting for the betting point spreads and obtain qualitatively similar results.

daily return and several firm characteristics used in this study. The daily return (*RETURN*) is the stock return for our sample firms on the first trading day following the football game. We follow Baker and Wurgler (2006) and measure firm characteristics at the end of June prior to the football game. Firm size (*SIZE*) is market capitalization in millions. Firm age (*AGE*) is the number of years since the firm's first appearance in the CRSP returns. The book-to-market ratio (*B/M*) is the ratio of book equity to market equity. Return volatility (*VOLATILITY*) is the standard deviation of monthly returns over the 12 months ending in June before the football game. Asset tangibility (*TANGIBILITY*) is gross property, plant, and equipment scaled by lagged total assets. Firm profitability (*PROFITABILITY*) is measured by the average return on assets (ROA) for the three years before the football game, where ROA is defined as the ratio of earnings before interest and taxes (EBIT) to lagged total assets.[8] Dividend per share (*DP*S) is total cash dividend divided by the number of shares outstanding.

**[Insert Table I here]**

## IV. Sports Sentiment and Daily Stock Returns

### *A. Effects of Football Game Outcomes on Daily Stock Returns*

To examine whether locally headquartered companies where there are losing football teams exhibit differential return impacts, we regress *RETURN* against $D_{Loss}$, a dummy variable that equals one if the football team fails to cover the point spread (loses the game), and zero if it covers the point spread (wins the game). Panel A of Table II shows the impact of the football teams' game results on the next-day returns of their

[8] The results are similar if we measure profitability by the ROA for the year before the football game. The results are also similar when the ROA is defined as the ratio of operating income before depreciation (OIBD) or net income (NI) to lagged total assets.

locally headquartered stocks. The coefficient for the $D_{Loss}$ variable in Model 1 is negative and statistically significant at the 5% level.[9] Consistent with hypothesis 1, locally headquartered companies where there are losing teams experience significantly lower next-day returns than those companies where there are winning teams. Our evidence supports the view that the mood of local investors induced by sports effects has a significant impact on the returns of localized trading stocks.

**[Insert Table II here]**

In Model 2 of Panel A, we also control for day-of-the-week and month-of-the-year effects (Cross, 1973; Smirlock and Starks, 1986; Thaler, 1987a and 1987b) and effects of other U.S. sports games taking place on the same day as football games.[10] Dummy variables for Monday ($D_{Mon}$), January ($D_{Jan}$), and other sports games ($D_{OG}$) as well as firm dummy variables are included in the regressions. Model 2 shows that the coefficient for the $D_{Loss}$ variable remains significantly negative at the 5% level. Mondays exhibit significantly lower returns, while Januaries exhibit significantly higher returns, consistent with previous evidence.[11] The effects of other sports games are not significant.[12]

While we find that football game results seem to affect stock returns, it should be noted that this phenomenon does not present an easy profitable opportunity. The coefficient of $D_{Loss}$ in Model 2 is –0.08%, indicating that going long the firms

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[9] Our conclusions remain unchanged if the *t*-values in regressions are computed with heteroskedasticity-consistent standard errors (White, 1980).

[10] The other U.S. major sports include baseball games played in the major leagues, basketball games in the National Basketball Association, and hockey games in the National Hockey League.

[11] See Rozeff and Kinney (1976), French (1980), Keim (1983), De Bondt and Thaler (1987), Lakonishok and Smidt (1988), Bessembinder and Hertzel (1993), and Haugen and Jorion (1996).

[12] The coefficients on firm dummy variables are not presented in order to save space.

headquartered in the area of winning teams and simultaneously shorting firms in the area of losing teams would generate a daily return of only 0.08%. Assuming a daily investment frequency and after considering a 0.5% one-way transaction cost, the excess return is not economically significant.[13] Even traders who trade at low transaction costs would find it difficult to take advantage of the price drop. This finding is consistent with Edmans et al. (2007).

It is interesting to test the effect of Super Bowl games. The outcome of the Super Bowl is an important event for a city that creates strong sentiments among the local fans (Pavelchak et al., 1988; Newell et al., 2001; Tobar, 2006). In 2006, an estimated 90.7 million people watched the Super Bowl with a TV rating of 41.6, and a total of 141.4 million people watched at least some part of the game.[14] In Model 3 of Panel A, we include an additional interaction term $D_{Loss} \times D_{SB}$, where $D_{SB}$ is a dummy variable for Super Bowl games. The coefficient of $D_{Loss} \times D_{SB}$ is negative and statistically significant at the 1% level. The result shows that locally headquartered companies, where there are losing teams in Super Bowl games, experience significantly lower next-day returns, an effect that is much stronger than losses for other games.

To investigate hypothesis 2, we regress *RETURN* against two dummy variables, $D_{SL1}$ and $D_{SL2}$. $D_{SL1}$ equals one if the football team covers the point spread in the previous game but fails to cover the point spread in the current game, and zero otherwise. $D_{SL2}$ equals one if the team fails to cover the point spread in both the previous and the current games (i.e., the team loses at least two games in a row), and zero otherwise. Panel B of

[13] Berkowitz et al. (1988) estimate one way transaction costs of 23 basis points for institutional investors. Jegadeesh and Titman (1993) use 0.5% as the assumed transaction cost when they examine the economic significance of trading strategies.
[14] See *CBS News* (Feb. 6, 2006) (www.cbsnews.com/stories/2006/02/06/superbowl/main1288104.shtml).

Table II shows the impact of successive losses. The coefficient for the $D_{SL2}$ variable in Model 1 is negative and statistically significant at the 1% level, while $D_{SL1}$ becomes statistically insignificant. This evidence suggests that game losses have a more negative effect on stock returns when football teams experience a successive loss of games. Our results support the hypothesis that a stream of losses in sports tends to generate more bearish sentiments among investors (Gilovich et al., 1985; Camerer, 1989; Tassoni, 1996; Offerman and Sonnemans, 2004).

In Model 2 of Panel B, we also include $D_{Mon}$, $D_{Jan}$, $D_{OG}$, and firm dummy variables to control for other potentially influential variables. $D_{SL2}$ remains significantly negative at the 1% level, and $D_{SL1}$ remains statistically insignificant. Our findings remain robust after controlling for other potentially influential variables. The evidence in Model 2 again supports the view that investors feel worse when their football teams lose more games in a row, resulting in a greater negative impact on the returns of locally headquartered stocks.

*B. Role of Firm Characteristics*

To investigate how firm characteristics affect the relation between football game outcomes and stock returns, we regress *RETURN* against $D_{Loss}$ and $D_{Loss} \times FC$, where *FC* equals one if the stocks of firms are more likely to be affected by sports sentiment, and zero otherwise. If the coefficient for the interaction term $D_{Loss} \times FC$ is significantly negative, the results would support the hypothesis that the negative effects of football game losses on returns are stronger for companies that are more vulnerable to shifts in investor sentiment. We also include $D_{Mon}$, $D_{Jan}$, $D_{OG}$, and firm dummy variables in these regressions to control for other potential explanatory variables.

We follow Baker and Wurgler (2006) and consider the firm characteristics: firm size (*SIZE*), firm age (*AGE*), book-to-market ratio (*B/M*), return volatility (*VOLATILITY*), asset tangibility (*TANGIBILITY*), firm profitability (*PROFITABILITY*), and dividend payment (*DPS*). The sample median of each firm characteristic, except for *DPS*, at the end of June prior to each football season is used to classify the sample firms into two subsamples. If *SIZE, AGE, B/M, TANGIBILITY*, or *PROFITABILITY* is lower than the sample median or *VOLATILITY* is greater than the sample median, the firm's stock is more likely to be affected by sports sentiment, and hence *FC* equals one. Likewise, if *DPS* equals zero, the firm is a non-dividend-paying firm, and *FC* equals one.

Table III presents the impact of firm characteristics on the relation between football game outcomes and stock returns. Model 1 in each panel shows that the coefficient for the interaction term $D_{Loss} \times FC$ is negative and statistically significant at the 10% level or better for *SIZE*, *VOLATILITY*, and *DPS*, while $D_{Loss}$ becomes statistically insignificant in all regressions. Our results indicate that football game losses have significantly stronger negative effects on stock returns for smaller firms, non-dividend-paying firms, and firms with higher volatility. The evidence is consistent with the arguments by Baker and Wurgler (2006) that the stocks of these firms are more likely to be affected by sports sentiment, because they are vulnerable to shifts in the propensity to speculate, are difficult to arbitrage, and have subjective valuations.

**[Insert Table III here]**

Since the two explanatory variables $D_{Loss}$ and $D_{Loss} \times FC$ in all Models 1 are correlated, we also provide estimates in Table III that include only $D_{Loss} \times FC$. Models 2 show that the interaction terms $D_{Loss} \times FC$ for *SIZE*, *VOLATILITY*, and *DPS* remain significantly negative. The interaction terms for *AGE*, *TANGIBILITY*, and *PROFITABILITY* are now significantly negative. This suggests that the effects of football game outcomes on stock returns are also significantly stronger for younger firms and firms with less asset tangibility and profitability.

## V. Intraday Returns and Trading Variables

### *A. Effects of Football Game Outcomes on Intraday Patterns of Stock Returns*

We examine how sports outcomes affect intraday returns on the first trading day following the football game by splitting a trading day (9:30-16:00) into thirteen 30-minute intervals. The interval return (*INTRET*) is calculated as the natural log of the prices that are nearest to the beginning of the interval subtracted from the natural log of the prices that are nearest to the end of the interval. We then regress *INTRET* against $D_{Loss}$ for four trading periods: 9:30-10:00 (the market opening trading period), 10:00-11:00, 11:00-15:00, and 15:00-16:00 (the market closing trading period).[15] We include the control variables, $D_{Mon}$, $D_{Jan}$, $D_{OG}$, firm dummy variables, and dummy variables for trading intervals. Table IV presents the results.[16]

**[Insert Table IV here]**

[15] When we partition a trading day into four trading periods, a 30-minute first period followed by three equal-length periods of two hours each, our conclusions remain the same.

[16] The baseline trading interval is the first 30-minute interval of each regression. Interval dummies are included in the regressions for the trading periods of 10:00-11:00, 11:00-15:00, and 15:00-16:00, except for the trading period of 9:30-10:00. The coefficients on firm dummies and interval dummies are not presented in order to save space.

Table IV shows that the coefficient for the $D_{Loss}$ variable is significantly negative only during the market opening period, consistent with hypothesis 4. For other intraday trading intervals, football game outcomes do not significantly influence stock returns. That is, while sports outcomes affect stock returns, the effect is only short-term. The evidence is consistent with the hypothesis that investors experiencing psychological changes from the outcomes of sports games act on their moods only in the opening trades of the next trading day, and these transient changes quickly become less important as more information comes to the market during the trading day (Lo and Repin, 2002; Chang et al., 2008). Our findings on the very short-run impact of football game outcomes on stock returns suggest that psychological factors have only a fleeting influence on stock returns. Evidence of a very short-term sports sentiment effect provides further support for our argument above that trading on the effect does not seem to be profitable.

We also examine the effect of Super Bowl games on intraday returns. In all Models 3 of Table 4, we include an additional interaction term $D_{Loss} \times D_{SB}$. We find that the coefficient of $D_{Loss} \times D_{SB}$ is significantly negative during the market opening period. For the other intraday trading intervals, however, the Super Bowl game outcomes do not significantly influence stock returns. The result indicates that the stronger effects of the Super Bowl game losses are pronounced only at the market open.

We further closely examine shorter intervals during the first 30 minutes after the market open. Table V reports five-minute results. During the first five minutes after the market open, the coefficient for the $D_{Loss}$ variable is significantly negative. This significance then diminishes quickly, and the $D_{Loss}$ variable becomes statistically insignificant for other intraday trading intervals. The findings in Table V provide further support for our results in Table IV. Sports sentiment has a significant influence on stock returns only during the first few minutes after the market open, and its impact is dissipated quickly as more information comes to the market throughout the day.

**[Insert Table V here]**

In Table VI, we investigate the impact of successive game losses on intraday returns. Regressions of *INTRET* against $D_{SL1}$, $D_{SL2}$, and control variables for four trading periods yield a significantly negative coefficient for the $D_{SL2}$ variable only during the market opening period, while $D_{SL1}$ is statistically insignificant in all four trading periods. As in the results for daily returns, our intraday evidence indicates stronger negative effects of game losses on stock returns when football teams experience a run of losses. These effects are only short-term, however, in that a stream of losses in sports games tends to generate more bearish sentiments of investors only at market opening periods.

**[Insert Table VI here]**

In Table VII, we examine how firm characteristics affect the relation between football game outcomes and intraday returns. Since football game outcomes affect next-day stock returns only during the market opening period, we focus on the regressions of *INTRET* against $D_{Loss}$, $D_{Loss} \times FC$, and control variables for the trading period of 9:30-10:00. The Model 1 results in Table VII show that the coefficient for the interaction term $D_{Loss} \times FC$ is significantly negative at the 10% level or better for *SIZE*, *AGE*, *VOLATILITY*, and *PROFITABILITY*, while $D_{Loss}$ is statistically insignificant in all regressions. For the Model 2 estimates that include only $D_{Loss} \times FC$, the results are similar, except that the interaction terms for *B/M* and *DPS* are now significantly negative. The results indicate that the negative effects of football game losses on stock returns at the market open are significantly stronger for small firms, young firms, high-growth firms, non-dividend-paying firms, and firms with high return volatility and low asset profitability. The evidence is again consistent with Baker and Wurgler (2006) that these firms' stocks are vulnerable to shifts in the propensity to speculate, are difficult to arbitrage, and have subjective valuations. Therefore, they are more likely to be affected by sports-induced sentiment.

**[Insert Table VII here]**

*B. Effects of Football Game Outcomes on Trading Behavior at the Market Open*

Since stock price changes are caused by investor trading activities, and football game outcomes affect stock returns only at the market open, we investigate how sports sentiment affects investor trading activity during the opening period (9:30-10:00) of the first trading day following the game. Trading measures include order imbalance, turnover ratio, market depth, and spread variables. We calculate two order imbalance ratios. The first is based on trading volume (*OISVOL*), and is calculated as the trading volume of seller-initiated trades divided by the total trading volume in the opening period. The second is based on number of trades (*OISNUM*), and is calculated as the number of seller-initiated trades divided by the total number of trades in the opening period.[17] For variables related to trading volume in the opening period, we calculate two turnover

[17] We use the Lee and Ready (1991) algorithm for signing trades.

ratios, average trading volume per trade (*TURNPER*) and cumulative trading volume (*TURN*), each scaled by number of firm shares outstanding at the end of the previous month. Market depth (*DEPTH*) in the opening period is measured by the average quote size, defined as the sum of the bid size and ask size. As spreads are highly serially correlated and exhibit strong intraday patterns, we must control for autocorrelation and seasonality. We follow Chordia et al. (2002) and Goetzmann and Zhu (2005) and examine the difference between the spread in the opening period and the spread in the same interval on the prior trading day. We calculate two first-difference spread measures, the percentage effective (*DIF_ES*) and percentage quoted (*DIF_QS*) first-difference spreads. *DIF_ES* is defined as twice the absolute value of the difference between the trading price and the mid-point of the ask and the bid prices, scaled by the mid-point of the ask and the bid. *DIF_QS* is the difference between the ask price and the bid price scaled by the mid-point of the ask and the bid.

We regress each trading variable against $D_{Loss}$ and control variables ($D_{Mon}$, $D_{Jan}$, $D_{OG}$, and firm dummy variables). Table VIII presents the results. When the football teams lose games, there are significantly more seller-initiated trades, lower turnover ratios, and less market depth for locally headquartered stocks during the market opening period of the next trading day. This evidence is consistent with the intraday return evidence presented in Table IV. As investors are in a poorer mood around the market open, because of game losses the previous day, they tend to be pessimistic, less inclined to trade, and particularly less interested in buying shares, resulting in lower stock returns during the opening interval (Loughran and Schultz, 2004; Goetzmann and Zhu, 2005; Chang et al., 2008). We do not find that spread variables are significantly related to football game outcomes.

**[Insert Table VIII here]**

Table VIII also reports how investor types relate to the negative effects of football game losses on the trading volume of locally headquartered stocks at the market open. We define *NIVOL* as non-institutional investor trading volume divided by total trading volume in the opening period. We follow Lee and Radhakrishna (2000) and define institutional investor trading as trades over $20,000.[18] We then regress *NIVOL* against $D_{Loss}$ and control variables. Table VIII shows a negative coefficient for the $D_{Loss}$ variable in this regression (statistically significant at the 1% level). Thus the negative effects of football game losses on trading volume around the market open appear significantly stronger for non-institutional traders than for institutional traders, consistent with hypothesis 6. When non-institutional investors are in a bad mood induced by game losses, they are more likely to be influenced by sports results and trade less.

## VI. Sports Sentiment and Stock Returns of NYSE Stocks

Our analysis so far has focused on Nasdaq firms, whose investors are likely to exhibit strong patterns of localized trading. A crucial question to address is whether the results of football games, which are predominantly contested on a club level, affect the next-day returns of firms listed on the NYSE. Many NYSE stocks are well known internationally and they may even be foreign firms. As Bessembinder (2003) notes, the

[18] When we follow Campbell et al. (2004) and define institutional trading as trades over $30,000, the results are similar.

NYSE competes order flows from all over the country with five regional stock markets and the Nasdaq. Bacidore et al. (2005) show that cross-border listing and trading is a growing part of the NYSE's business. At the end of 2002, 473 firms from 54 countries had NYSE-listed securities. Saunders (1993) also recognizes that a large proportion of orders on the NYSE come from places outside New York City. The relation between football game outcomes and stock returns would be expected to be weak for NYSE firms whose orders come from all over the country and all over the world.

We examine the impact of football game outcomes on the returns of NYSE firms whose headquarters have the same first three-digit zip codes as the cities of NFL football teams. The sample period runs from September 1994 through December 2004. Panel A of Table IX shows the results for stock returns throughout the entire trading day following a game. We find no significant impact of game outcomes on the daily returns of NYSE stocks. The coefficient for the $D_{Loss}$ variable is statistically insignificant in both Model 1 without control variables and Model 2 with control variables. Our findings support the argument that trading in Nasdaq stocks is more localized. Local football game results have a more pronounced impact on Nasdaq stocks than on NYSE stocks.

**[Insert Table IX here]**

Panel B reports the results for examination of the returns on NYSE stocks during the opening period (9:30-10:00) of the first trading day following the football game. Again, we find that during the first 30 minutes after the market open, the coefficient for the $D_{Loss}$ variable is significantly insignificant. The results are different from those for

Nasdaq stocks, and again support a weak relation between football game outcomes and stock returns for NYSE stocks.

## VII. Conclusions

We have conducted firm-level analysis of the relation between National Football League game outcomes and the return patterns and trading behavior of Nasdaq firms whose headquarters are located in the same geographic areas as the teams. We show that losses by local teams precede significantly lower next-day stock returns for locally headquartered stocks. This result suggests that the moods of local investors induced by sports outcomes have a significant impact on the returns of localized trading stocks. We also find significantly stronger negative effects of football game losses on stock returns when teams experience a run of losses. Our findings suggest that successive losses tend to generate more bearish sentiments in investors, thus resulting in lower stock returns.

We further document that the impact of football game results on the stock returns of locally headquartered stocks depends on firm characteristics. The negative effects of losses on returns are significantly stronger for smaller firms, younger firms, non-dividend-paying firms, and firms with higher return volatility and less asset tangibility and profitability. Such firms are more likely to be affected by sports sentiment because they are vulnerable to shifts in the propensity to speculate and difficult to arbitrage, and are valued subjectively.

We then examine the effects of game outcomes on the intraday returns of locally headquartered stocks on the first trading day following the game. We find that losses significantly and negatively influence next-day stock returns only at the market open.

The influence becomes insignificant for later trading intervals. Our findings suggest that investors experiencing feelings on the outcomes of a game act on their moods in the opening trades, but the impact of these changes on returns is transient, vanishing quickly as more information arrives in the market during the trading day. As in the results for daily returns, we also find significantly stronger negative effects of game losses on stock returns at the market open when teams experience several losses in a row. These effects during the market opening period are also significantly stronger for the firms that are more vulnerable to shifts in investor sentiment.

During the market opening period of the next trading day after a loss, there are significantly more seller-initiated trades along with lower turnover ratios and market depth for locally headquartered stocks. The findings suggest that football game losses make investors pessimistic at the market open, dampening their inclination to trade, especially to buy. We also find significantly stronger negative effects of game losses on trading volume around the market open for non-institutional traders than for institutional traders, because individual traders are most likely to be influenced by sports sentiment.

Finally, results of football game losses on the next-day stock returns of nearby NYSE-listed firms are different. Football game outcomes have no significant impact on the returns of NYSE stocks. These results hold for stock returns throughout the day and during the opening trading interval. As trading in Nasdaq stocks is more localized, local football game results have a more pronounced impact on Nasdaq stocks than on NYSE stocks.

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## Table I. Sample Distribution and Summary Statistics

This table presents sample distributions by year and summary statistics for daily stock return and several firm characteristics used in this study. To be included in the final sample, a firm must meet several criteria: (1) Shares of the firm are traded on the Nasdaq; (2) the firm's headquarter has the same first three-digit zip code as the city of an NFL football team; and (3) the firm has data available on the CRSP and the Compustat databases. The daily return (*RETURN*) is the stock return for sample firms on the first trading day following the football game. Firm characteristics are measured at the end of June prior to the football game. Firm size (*SIZE*) is market capitalization in millions. Firm age (*AGE*) is number of years since the firm's first appearance on the CRSP. The book-to-market ratio (*B/M*) is the ratio of book equity to market equity. Return volatility (*VOLATILITY*) is standard deviation of monthly returns over the 12 months ending in the June prior to the football game. Asset tangibility (*TANGIBILITY*) is gross property, plant, and equipment scaled by lagged total assets. Firm profitability (*PROFITABILITY*) is measured by the average return on assets (ROA) for the three years before the football game, where ROA is defined as the ratio of earnings before interest and taxes (EBIT) to lagged total assets. Dividend per share (*DP*S) is total cash dividend divided by number of shares outstanding. The number of observations in Panel B varies across variables because of data availability.

***Panel A. Sample Distribution by Year***

| Year | Number of Observations | Percent of Sample |
|---|---|---|
| 1994 | 4,582 | 4.9 |
| 1995 | 5,728 | 6.1 |
| 1996 | 6,655 | 7.1 |
| 1997 | 7,384 | 7.9 |
| 1998 | 8,132 | 8.7 |
| 1999 | 8,763 | 9.4 |
| 2000 | 10,503 | 11.3 |
| 2001 | 9,187 | 9.8 |
| 2002 | 10,986 | 11.8 |
| 2003 | 11,056 | 11.8 |
| 2004 | 10,364 | 11.1 |
| Total | 93,340 | 100.0 |

***Panel B. Summary Statistics***

| Variable | Mean | Q1 | Median | Q3 | Standard Deviation | N |
|---|---|---|---|---|---|---|
| *RETURN* (%) | 0.04 | -2.08 | 0.00 | 1.83 | 5.07 | 93,340 |
| *SIZE* ($millions) | 472 | 32 | 98 | 337 | 1,207 | 93,340 |
| *AGE* (years) | 8.53 | 8.00 | 10.00 | 10.00 | 2.23 | 93,340 |
| *B/M* | 0.71 | 0.26 | 0.53 | 0.93 | 0.77 | 89,447 |
| *VOLATILITY* (%) | 17.54 | 9.13 | 14.65 | 22.43 | 11.70 | 92,030 |
| *TANGILIBILITY* (%) | 37.07 | 11.89 | 27.02 | 53.97 | 32.36 | 85,464 |
| *PROFITABILITY* (%) | -5.14 | -7.13 | 2.59 | 8.95 | 29.05 | 92,968 |
| *DPS* ($) | 0.13 | 0.00 | 0.00 | 0.00 | 0.34 | 91,836 |

## Table II. Effects of Football Game Outcomes on Daily Stock Returns

This table presents regression analyses of *RETURN* (in percentage), which is the daily stock return for sample firms on the first trading day following the football game. To be included in the final sample, a firm must meet several criteria: (1) Shares of the firm are traded on the Nasdaq; (2) the firm's headquarter has the same first three-digit zip code as the city of an NFL football team; and (3) the firm has data available on the CRSP and the Compustat databases. $D_{Loss}$ equals one if the football team fails to cover the point spread (loses the game), and zero if it covers the point spread (wins the game). $D_{SB}$ equals one for a Super Bowl game, and zero otherwise. $D_{SL1}$ equals one if the football team covers the point spread in the previous game but fails to cover the point spread in the current game, and zero otherwise. $D_{SL2}$ equals one if the team fails to cover the point spread both in the previous and current games (i.e., the team loses at least two games in a row), and zero otherwise. The control variables are dummy variables for Monday ($D_{Mon}$), January ($D_{Jan}$), and other U.S. major sports games ($D_{OG}$) as well as firm dummy variables. The coefficients on firm dummy variables are not presented in order to save space. Numbers in parentheses are *t*-statistics. ***, **, and * represent 1%, 5%, and 10% levels, respectively.

***Panel A. Effects of Game Losses***

| | Independent Variable | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Model | *Intercept* | $D_{Loss}$ | $D_{Loss} \times D_{SB}$ | $D_{Mon}$ | $D_{Jan}$ | $D_{OG}$ | Adj.$R^2$ (%) | N |
| 1 | 0.7449** | -0.0675** | | | | | 0.27 | 93,340 |
| | (1.98) | (-1.97) | | | | | | |
| 2 | 0.9500** | -0.0800** | | -0.3030*** | 0.3154*** | -0.0087 | 0.32 | 93,340 |
| | (2.50) | (-2.33) | | (-6.07) | (4.02) | (-0.22) | | |
| 3 | 0.9434** | -0.0751** | -1.0865*** | -0.2987*** | 0.3423*** | -0.0115 | 0.33 | 93,340 |
| | (2.48) | (-2.19) | (-2.93) | (-5.98) | (4.33) | (-0.30) | | |

***Panel B. Effects of Successive Game Losses***

| | Independent Variable | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Model | *Intercept* | $D_{SL1}$ | $D_{SL2}$ | $D_{Mon}$ | $D_{Jan}$ | $D_{OG}$ | Adj.$R^2$ (%) | N |
| 1 | 0.7487** | 0.0398 | -0.1758*** | | | | 0.29 | 93,340 |
| | (1.99) | (0.95) | (-4.20) | | | | | |
| 2 | 0.9422** | 0.0110 | -0.1708*** | -0.2887*** | 0.2987*** | -0.0065 | 0.34 | 93,340 |
| | (2.48) | (0.26) | (-4.08) | (-5.76) | (3.80) | (-0.17) | | |

## Table III. Effects of Firm Characteristics on the Relation between Football Game Outcomes and Daily Stock Returns

This table shows how firm characteristics affect the relation between football game outcomes and stock returns. The dependent variable is *RETURN* (in percentage), which is the daily stock return for sample firms on the first trading day following the football game. To be included in the final sample, a firm must meet several criteria: (1) Shares of the firm are traded on the Nasdaq; (2) the firm's headquarter has the same first three-digit zip code as the city of an NFL football team; and (3) the firm has data available on the CRSP and the Compustat databases. *RETURN* is regressed against $D_{Loss}$, $D_{Loss} \times FC$, and control variables. $D_{Loss}$ equals one if the football team fails to cover the point spread (loses the game), and zero if it covers the point spread (wins the game). *FC* is a dummy variable that equals one if the stocks of firms are more likely to be affected by sports sentiment, and zero otherwise. Firm characteristics include *SIZE*, *AGE*, *B/M*, *VOLATILITY*, *TANGIBILITY*, *PROFITABILITY*, and *DPS*, which are defined in Table I. The sample median of each firm characteristic, except for *DPS*, at the end of June prior to each football season is used to classify the sample firms into two subsamples. If *SIZE*, *AGE*, *B/M*, *TANGIBILITY*, or *PROFITABILITY* is lower than the sample median or *VOLATILITY* is greater than the sample median, the firm's stock is more likely to be affected by sports sentiment, and hence *FC* equals one. Likewise, if *DPS* equals zero, the firm is a non-dividend-paying firm, and *FC* equals one. The control variables are dummy variables for Monday ($D_{Mon}$), January ($D_{Jan}$), and other U.S. major sports games ($D_{OG}$) as well as firm dummy variables. The coefficients on firm dummy variables are not presented in order to save space. The number of observations varies across variables because of data availability. Numbers in parentheses are *t*-statistics. ***, **, and * represent 1%, 5%, and 10% levels, respectively.

| Model | Independent Variable | | | | | | Adj.$R^2$ (%) | N |
|---|---|---|---|---|---|---|---|---|
| | *Intercept* | $D_{Loss}$ | $D_{Loss} \times FC$ | $D_{Mon}$ | $D_{Jan}$ | $D_{OG}$ | | |
| ***Panel A. FC = 1 if SIZE < Sample Median*** | | | | | | | | |
| 1 | 0.3446*** | 0.0524 | -0.0987** | -0.3062*** | 0.3018*** | -0.0390 | 0.33 | 93,340 |
| | (6.77) | (0.67) | (-2.05) | (-6.07) | (3.77) | (-1.08) | | |
| 2 | 0.3496*** | | -0.0697*** | -0.3061*** | 0.3018*** | -0.0392 | 0.33 | 93,340 |
| | (6.94) | | (-3.34) | (-6.07) | (3.77) | (-1.08) | | |
| ***Panel B. FC = 1 if AGE < Sample Median*** | | | | | | | | |
| 1 | 0.3438*** | -0.1031 | 0.0083 | -0.3072*** | 0.3006*** | -0.0382 | 0.32 | 93,340 |
| | (6.77) | (-1.35) | (0.17) | (-6.10) | (3.76) | (-1.06) | | |
| 2 | 0.3325*** | | -0.0519** | -0.3060*** | 0.3003*** | -0.0381 | 0.32 | 93,340 |
| | (6.64) | | (-2.34) | (-6.08) | (3.75) | (-1.05) | | |
| ***Panel C. FC = 1 if B/M < Sample Median*** | | | | | | | | |
| 1 | -0.1289 | 0.0112 | -0.0710 | -0.3016*** | 0.3115*** | -0.0329 | 0.40 | 89,410 |
| | (-1.46) | (0.10) | (-1.03) | (-5.90) | (3.84) | (-0.90) | | |
| 2 | 0.2919*** | | -0.0057 | -0.2988*** | 0.3109*** | -0.0408 | 0.32 | 89,410 |
| | (5.71) | | (-0.27) | (-5.84) | (3.83) | (-1.11) | | |

**Table III (*Continued*)**

| Model | Independent Variable | | | | | | Adj.$R^2$ (%) | N |
|---|---|---|---|---|---|---|---|---|
| | *Intercept* | $D_{Loss}$ | $D_{Loss} \times FC$ | $D_{Mon}$ | $D_{Jan}$ | $D_{OG}$ | | |
| ***Panel D. FC = 1 if VOLATILITY > Sample Median*** | | | | | | | | |
| 1 | 0.1493* | 0.1519 | -0.1662** | -0.3072*** | 0.3020*** | -0.0394 | 0.33 | 91,990 |
| | (1.72) | (1.44) | (-2.44) | (-6.10) | (3.77) | (-1.09) | | |
| 2 | 0.3399*** | | -0.0573*** | -0.3072*** | 0.3007*** | -0.0383 | 0.33 | 91,990 |
| | (6.76) | | (-2.73) | (-6.10) | (3.76) | (-1.06) | | |
| ***Panel E. FC = 1 if TANGIBILITY < Sample Median*** | | | | | | | | |
| 1 | 0.2917*** | -0.0982 | -0.0049 | -0.2621*** | 0.3449*** | -0.0086 | 0.31 | 85,464 |
| | (5.00) | (-1.09) | (-0.09) | (-4.54) | (3.77) | (-0.21) | | |
| 2 | 0.2830*** | | -0.0590** | -0.2622*** | 0.3440*** | -0.0096 | 0.31 | 85,464 |
| | (4.90) | | (-2.48) | (-4.54) | (3.76) | (-0.23) | | |
| ***Panel F. FC = 1 if PROFITABILITY < Sample Median*** | | | | | | | | |
| 1 | 0.3500*** | -0.0914 | 0.0034 | -0.2862*** | 0.2699*** | -0.0201 | 0.31 | 81,825 |
| | (6.57) | (-1.14) | (0.07) | (-5.43) | (3.26) | (-0.54) | | |
| 2 | 0.3416*** | | -0.0480** | -0.2864*** | 0.2696*** | -0.0205 | 0.31 | 81,825 |
| | (6.47) | | (-2.18) | (-5.43) | (3.26) | (-0.55) | | |
| ***Panel G. FC = 1 if DPS = 0*** | | | | | | | | |
| 1 | 0.3362*** | 0.0406 | -0.0739* | -0.3034*** | 0.2930*** | -0.0239 | 0.32 | 91,836 |
| | (6.86) | (0.40) | (-1.66) | (-6.25) | (3.80) | (-0.69) | | |
| 2 | 0.3384*** | | -0.0533*** | -0.3036*** | 0.2930*** | -0.0237 | 0.33 | 91,836 |
| | (6.95) | | (-3.03) | (-6.25) | (3.80) | (-0.68) | | |

## Table IV. Effects of Football Game Outcomes on Intraday Returns

This table presents regression analyses of intraday returns for sample firms on the first trading day following the football game. To be included in the final sample, a firm must meet several criteria: (1) Shares of the firm are traded on the Nasdaq; (2) the firm's headquarter has the same first three-digit zip code as the city of an NFL football team; and (3) the firm has data available on the CRSP, Compustat, and TAQ databases. A trading day (9:30-16:00) is split into thirteen 30-minute intervals. The dependent variable is the interval return (*INTRET*) in percentage, which is calculated as the natural log of the prices that are nearest to the beginning of the interval subtracted from the natural log of the prices that are nearest to the end of the interval. $D_{Loss}$ equals one if the football team fails to cover the point spread (loses the game), and zero if it covers the point spread (wins the game). $D_{SB}$ equals one for a Super Bowl game, and zero otherwise. The control variables are dummy variables for Monday ($D_{Mon}$), January ($D_{Jan}$), and other U.S. major sports games ($D_{OG}$), firm dummy variables, and dummy variables indicating trading intervals (baseline comparison is to the first trading interval of each regression). Interval dummies are included in the regressions for the trading periods of 10:00-11:00, 11:00-15:00, and 15:00-16:00, except for the trading period of 9:30-10:00. The coefficients on firm dummies and interval dummies are not presented in order to save space. Numbers in parentheses are *t*-statistics. ***, **, and * represent 1%, 5%, and 10% levels, respectively.

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| ***Panel A. Trading Period: 9:30 – 10:00*** | | | | | | | | |
| | Independent Variable | | | | | | | |
| Model | *Intercept* | $D_{Loss}$ | $D_{Loss} \times D_{SB}$ | $D_{Mon}$ | $D_{Jan}$ | $D_{OG}$ | Adj.$R^2$ (%) | N |
| 1 | -2.1613* | -0.0600** | | | | | 1.46 | 38,248 |
| | (-1.84) | (-2.38) | | | | | | |
| 2 | -2.0013* | -0.0618** | | -0.1453*** | -0.3557*** | -0.0666** | 1.58 | 38,248 |
| | (-1.71) | (-2.34) | | (-3.24) | (-5.52) | (-2.08) | | |
| 3 | 0.2718 | -0.0406* | -0.7411*** | -0.0957*** | -0.2608*** | -0.0541** | 0.60 | 38,248 |
| | (0.51) | (-1.71) | (-2.90) | (-2.59) | (-4.86) | (-2.05) | | |
| ***Panel B. Trading Period: 10:00 – 11:00*** | | | | | | | | |
| | Independent Variable | | | | | | | |
| Model | *Intercept* | $D_{Loss}$ | $D_{Loss} \times D_{SB}$ | $D_{Mon}$ | $D_{Jan}$ | $D_{OG}$ | Adj.$R^2$ (%) | N |
| 1 | 0.8736*** | -0.0014 | | | | | 0.07 | 86,296 |
| | (3.31) | (-0.12) | | | | | | |
| 2 | 0.8950*** | 0.0007 | | -0.0193 | -0.1955*** | -0.0074 | 0.14 | 86,296 |
| | (3.39) | (0.06) | | (-1.07) | (-7.48) | (-0.57) | | |
| 3 | 0.8942*** | 0.0015 | -0.1602 | -0.0187 | -0.1930*** | -0.0078 | 0.14 | 86,296 |
| | (3.38) | (0.13) | (-1.25) | (-1.03) | (-7.36) | (-0.60) | | |

**Table IV (*Continued*)**

| ***Panel C. Trading Period: 11:00 – 15:00*** | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Independent Variable | | | | | | | |
| Model | *Intercept* | $D_{Loss}$ | $D_{Loss} \times D_{SB}$ | $D_{Mon}$ | $D_{Jan}$ | $D_{OG}$ | Adj.$R^2$ (%) | N |
| 1 | -0.0277 | -0.0019 | | | | | 0.02 | 352,516 |
| | (-0.28) | (-0.41) | | | | | | |
| 2 | -0.0195 | -0.0025 | | -0.0093 | 0.0243** | 0.0001 | 0.02 | 352,516 |
| | (-0.20) | (-0.53) | | (-1.30) | (2.33) | (0.02) | | |
| 3 | -0.0199 | -0.0021 | -0.0690 | -0.0090 | 0.0255** | 0.0000 | 0.02 | 352,516 |
| | (-0.20) | (-0.46) | (-1.38) | (-1.26) | (2.43) | (-0.01) | | |

| ***Panel D. Trading Period: 15:00 – 16:00*** | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Independent Variable | | | | | | | |
| Model | *Intercept* | $D_{Loss}$ | $D_{Loss} \times D_{SB}$ | $D_{Mon}$ | $D_{Jan}$ | $D_{OG}$ | Adj.$R^2$ (%) | N |
| 1 | -0.0528 | -0.0048 | | | | | 0.27 | 99,409 |
| | (-0.30) | (-0.47) | | | | | | |
| 2 | 0.0033 | -0.0072 | | -0.0577*** | 0.0458* | -0.0027 | 0.29 | 99,409 |
| | (0.02) | (-0.70) | | (-3.59) | (1.93) | (-0.23) | | |
| 3 | 0.0024 | -0.0065 | -0.1498 | -0.0571*** | 0.0484** | -0.0030 | 0.29 | 99,409 |
| | (0.01) | (-0.63) | (-1.35) | (-3.55) | (2.03) | (-0.26) | | |

## Table V. Effects of Football Game Outcomes on Stock Returns during the Market Opening Period

This table presents regression analyses of stock returns during the market opening period (9:30-10:00) for sample firms on the first trading day following the football game. To be included in the final sample, a firm must meet several criteria: (1) Shares of the firm are traded on the Nasdaq; (2) the firm's headquarter has the same first three-digit zip code as the city of an NFL football team; and (3) the firm has data available on the CRSP, Compustat, and TAQ databases. The dependent variable is the five-minute return in percentage during the first 30 minutes after the market open. $D_{Loss}$ equals one if the football team fails to cover the point spread (loses the game), and zero if it covers the point spread (wins the game). The control variables are dummy variables for Monday ($D_{Mon}$), January ($D_{Jan}$), and other U.S. major sports games ($D_{OG}$) as well as firm dummy variables. The coefficients on firm dummies are not presented in order to save space. Numbers in parentheses are *t*-statistics. ***, **, and * represent 1%, 5%, and 10% levels, respectively.

| | Independent Variable | | | | | | |
|---|---|---|---|---|---|---|---|
| Trading Interval | *Intercept* | $D_{Loss}$ | $D_{Mon}$ | $D_{Jan}$ | $D_{OG}$ | Adj. $R^2$ (%) | N |
| 9:30 – 9:35 | 0.0038 | -0.0441** | -0.0631* | 0.0480 | -0.0198 | 0.91 | 28,795 |
| | (0.00) | (-2.15) | (-1.92) | (1.04) | (-0.82) | | |
| 9:35 – 9:40 | 0.023 | -0.0105 | -0.0327 | -0.0593* | -0.0079 | 1.48 | 34,455 |
| | (0.03) | (-0.69) | (-1.37) | (-1.75) | (-0.44) | | |
| 9:40 – 9:45 | 0.0242 | -0.0083 | -0.0112 | -0.0983*** | -0.0138 | 1.36 | 37,878 |
| | (0.04) | (-0.62) | (-0.54) | (-3.34) | (-0.88) | | |
| 9:45 – 9:50 | -2.4208*** | -0.0092 | -0.0325* | -0.0616** | -0.0178 | 0.69 | 40,502 |
| | (-5.24) | (-0.78) | (-1.78) | (-2.35) | (-1.28) | | |
| 9:50 – 9:55 | 4.1161*** | -0.0071 | 0.0031 | -0.0232 | -0.0006 | 1.34 | 42,599 |
| | (10.02) | (-0.64) | (0.18) | (-0.95) | (-0.04) | | |
| 9:55 – 10:00 | 0.0073 | -0.0048 | 0.0097 | -0.0461* | -0.0033 | 1.05 | 44,349 |
| | (0.02) | (-0.45) | (0.59) | (-1.95) | (-0.26) | | |

## Table VI. Effects of Successive Football Game Losses on Intraday Returns

This table shows how football game results affect intraday returns following game days when football teams experience a run of losses. To be included in the final sample, a firm must meet several criteria: (1) Shares of the firm are traded on the Nasdaq; (2) the firm's headquarter has the same first three-digit zip code as the city of an NFL football team; and (3) the firm has data available on the CRSP, Compustat, and TAQ databases. A trading day (9:30-16:00) is split into thirteen 30-minute intervals. The dependent variable is the interval return (*INTRET*) in percentage, which is calculated as the natural log of the prices that are nearest to the beginning of the interval subtracted from the natural log of the prices that are nearest to the end of the interval. $D_{SL1}$ equals one if the football team covers the point spread in the previous game but fails to cover the point spread in the current game, and zero otherwise. $D_{SL2}$ equals one if the team fails to cover the point spread in both the previous and the current games (i.e., the team loses at least two games in a row), and zero otherwise. The control variables are dummy variables for Monday ($D_{Mon}$), January ($D_{Jan}$), and other U.S. major sports games ($D_{OG}$), firm dummy variables, and dummy variables indicating trading intervals (baseline comparison is to the first trading interval of each regression). Interval dummies are included in the regressions for the trading periods of 10:00-11:00, 11:00-15:00, and 15:00-16:00, except for the trading period of 9:30-10:00. The coefficients on firm dummies and interval dummies are not presented in order to save space. Numbers in parentheses are *t*-statistics. ***, **, and * represent 1%, 5%, and 10% levels, respectively.

| | Independent Variable | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Trading Interval | *Intercept* | $D_{SL1}$ | $D_{SL2}$ | $D_{Mon}$ | $D_{Jan}$ | $D_{OG}$ | Adj.$R^2$ (%) | N |
| 9:30 – 10:00 | -1.9985* | -0.0520 | -0.0720** | -0.1439*** | -0.3572*** | -0.0666** | 1.58 | 38,248 |
| | (-1.71) | (-1.49) | (-2.03) | (-3.20) | (-5.53) | (-2.08) | | |
| 10:00–11:00 | 1.2079*** | 0.0274 | -0.0208 | -0.0211 | -0.2152*** | -0.0097 | 0.25 | 86,296 |
| | (3.79) | (1.60) | (-1.20) | (-0.97) | (-6.82) | (-0.61) | | |
| 11:00–15:00 | 0.0665 | 0.0012 | -0.0097 | -0.0088 | 0.0282** | 0.0004 | 0.08 | 352,516 |
| | (0.55) | (0.17) | (-1.39) | (-1.00) | (2.19) | (0.06) | | |
| 15:00–16:00 | -0.1417 | 0.0034 | -0.0201 | -0.0552*** | 0.0643** | 0.0084 | 0.36 | 99,409 |
| | (-0.65) | (0.22) | (-1.29) | (-2.79) | (2.21) | (0.59) | | |

**Table VII. Effects of Firm Characteristics on the Relation between Football Game Outcomes and Stock Returns during the Market Opening Period**

This table shows how firm characteristics affect the relation between football game outcomes and stock returns during the market opening period (9:30-10:00). To be included in the final sample, a firm must meet several criteria: (1) Shares of the firm are traded on the Nasdaq; (2) the firm's headquarter has the same first three-digit zip code as the city of an NFL football team; and (3) the firm has data available on the CRSP, Compustat, and TAQ databases. The dependent variable is the stock return in percentage during the first 30 minutes after the market open. The independent variables include $D_{Loss}$, $D_{Loss} \times FC$, and control variables. $D_{Loss}$ equals one if the football team fails to cover the point spread (loses the game), and zero if it covers the point spread (wins the game). *FC* is a dummy variable that equals one if the stocks of firms are more likely to be affected by sports sentiment, and zero otherwise. Firm characteristics include *SIZE*, *AGE*, *B/M*, *VOLATILITY*, *TANGIBILITY*, *PROFITABILITY*, and *DPS*, which are defined in Table I. The sample median of each firm characteristic, except for *DPS*, at the end of June prior to each football season is used to classify the sample firms into two subsamples. If *SIZE*, *AGE*, *B/M*, *TANGIBILITY*, or *PROFITABILITY* is lower than the sample median or *VOLATILITY* is greater than the sample median, the firm's stock is more likely to be affected by sports sentiment, and hence *FC* equals one. Likewise, if *DPS* equals zero, the firm is a non-dividend-paying firm, and *FC* equals one. The control variables are dummy variables for Monday ($D_{Mon}$), January ($D_{Jan}$), and other U.S. major sports games ($D_{OG}$) as well as firm dummy variables. The coefficients on firm dummy variables are not presented in order to save space. The number of observations varies across variables because of data availability. Numbers in parentheses are *t*-statistics. ***, **, and * represent 1%, 5%, and 10% levels, respectively.

| | Independent Variable | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Model | *Intercept* | $D_{Loss}$ | $D_{Loss} \times FC$ | $D_{Mon}$ | $D_{Jan}$ | $D_{OG}$ | Adj.$R^2$ (%) | N |
| | | | ***Panel A. FC = 1 if SIZE < Sample Median*** | | | | | |
| 1 | 0.0856** | 0.0562 | -0.0693* | -0.1246*** | -0.3357*** | -0.1003*** | 0.97 | 36,186 |
| | (2.09) | (0.97) | (-1.67) | (-3.08) | (-5.76) | (-3.76) | | |
| 2 | 0.0913** | | -0.0318* | -0.1252*** | -0.3356*** | -0.1005*** | 0.97 | 36,186 |
| | (2.25) | | (-1.71) | (-3.09) | (-5.76) | (-3.76) | | |
| | | | ***Panel B. FC = 1 if AGE < Sample Median*** | | | | | |
| 1 | 0.0563 | 0.0870 | -0.0768** | -0.0940** | -0.2819*** | -0.0773*** | 0.92 | 36,197 |
| | (1.47) | (1.59) | (-2.31) | (-2.49) | (-5.14) | (-3.10) | | |
| 2 | 0.0649* | | -0.0291** | -0.0946** | -0.2810*** | -0.0778*** | 0.92 | 36,197 |
| | (1.71) | | (-2.04) | (-2.51) | (-5.12) | (-3.12) | | |
| | | | ***Panel C. FC = 1 if B/M < Sample Median*** | | | | | |
| 1 | 0.0619 | 0.0479 | -0.0479 | -0.0974** | -0.2847*** | -0.0791*** | 0.92 | 35,756 |
| | (1.61) | (0.79) | (-1.39) | (-2.56) | (-5.16) | (-3.15) | | |
| 2 | 0.0652* | | -0.0228* | -0.0971** | -0.2847*** | -0.0787*** | 0.92 | 35,756 |
| | (1.70) | | (-1.69) | (-2.55) | (-5.16) | (-3.13) | | |

**Table VII (*Continued*)**

| Model | Independent Variable *Intercept* | $D_{Loss}$ | $D_{Loss} \times FC$ | $D_{Mon}$ | $D_{Jan}$ | $D_{OG}$ | Adj.$R^2$ (%) | N |
|---|---|---|---|---|---|---|---|---|
| | | | ***Panel D. FC = 1 if VOLATILITY > Sample Median*** | | | | | |
| 1 | 0.1299** | 0.1168 | -0.0936** | -0.0961** | -0.2803*** | -0.0791*** | 0.95 | 36,189 |
| | (2.02) | (1.52) | (-1.98) | (-2.55) | (-5.11) | (-3.17) | | |
| 2 | 0.0742* | | -0.0387*** | -0.0952** | -0.2804*** | -0.0786*** | 0.93 | 36,189 |
| | (1.95) | | (-2.80) | (-2.52) | (-5.11) | (-3.15) | | |
| | | | ***Panel E. FC = 1 if TANGIBILITY < Sample Median*** | | | | | |
| 1 | 0.0822* | -0.0124 | -0.0196 | -0.1228*** | -0.3696*** | -0.0964*** | 0.97 | 33,037 |
| | (1.88) | (-0.20) | (-0.51) | (-2.85) | (-5.97) | (-3.39) | | |
| 2 | 0.0810* | | -0.0265 | -0.1228*** | -0.3696*** | -0.0965*** | 0.97 | 33,037 |
| | (1.87) | | (-1.60) | (-2.85) | (-5.97) | (-3.39) | | |
| | | | ***Panel F. FC = 1 if PROFITABILITY < Sample Median*** | | | | | |
| 1 | 0.0659* | 0.0862 | -0.0826** | -0.0872** | -0.3041*** | -0.0714*** | 0.93 | 34,904 |
| | (1.71) | (1.60) | (-2.45) | (-2.30) | (-5.50) | (-2.86) | | |
| 2 | 0.0740* | | -0.0341** | -0.0872** | -0.3045*** | -0.0713*** | 0.93 | 34,904 |
| | (1.94) | | (-2.32) | (-2.30) | (-5.51) | (-2.85) | | |
| | | | ***Panel G. FC = 1 if DPS = 0*** | | | | | |
| 1 | 0.1663* | 0.1257 | -0.0874 | -0.0927** | -0.2829*** | -0.0696*** | 0.94 | 35,644 |
| | (1.94) | (1.15) | (-1.48) | (-2.55) | (-5.32) | (-2.89) | | |
| 2 | 0.0677* | | -0.0285** | -0.0927** | -0.2838*** | -0.0692*** | 0.92 | 35,644 |
| | (1.84) | | (-2.37) | (-2.54) | (-5.33) | (-2.87) | | |

## Table VIII. Effects of Football Game Outcomes on Trading Variables during the Market Opening Period

This table presents regression analyses of trading variables during the market opening period (9:30-10:00) for sample firms on the first trading day following the football game. To be included in the final sample, a firm must meet several criteria: (1) Shares of the firm are traded on the Nasdaq; (2) the firm's headquarter has the same first three-digit zip code as the city of an NFL football team; and (3) the firm has data available on the CRSP, Compustat, and TAQ databases. Two order imbalance ratios, one by trading volume (*OISVOL*) and one by number of trades (*OISNUM*), are defined. Order imbalance by trading volume is calculated as the trading volume of seller-initiated trades divided by the total trading volume. Order imbalance by number of trades is calculated as the number of seller-initiated trades divided by the total number of trades. Turnover per trade (*TURNPER*) is defined as the average trading volume per trade scaled by the outstanding shares at the end of last month. Cumulative turnover (*TURN*) is the total trading volume in the interval scaled by the outstanding shares at the end of the last month. Market depth (*DEPTH*) is the average quote size, defined as the sum of the bid size and ask size, in 100 shares. The first differences in effective spreads (*DIF_ES*) and quoted spreads (*DIF_QS*) are defined as the differences between the spread of the interval and that of the same interval of the previous trading day, to control for the well-known intraday seasonality and correlation in spreads. The percentage effective spread is defined as twice the absolute value of the difference between the trading price and the mid-point of the ask and the bid prices, scaled by the mid-point of the ask and the bid. The percentage quoted spread is the difference between the ask price and the bid price scaled by the mid-point of the ask and the bid. *NIVOL* is the non-institutional investor trading volume divided by the total trading volume in the opening period, where institutional investor trading is defined as trades over $20,000. $D_{Loss}$ equals one if the football team fails to cover the point spread (loses the game), and zero if it covers the point spread (wins the game). The control variables are dummy variables for Monday ($D_{Mon}$), January ($D_{Jan}$), and other U.S. major sports games ($D_{OG}$) as well as firm dummy variables. The coefficients on firm dummies are not presented in order to save space. The number of observations varies across variables because of data availability. Numbers in parentheses are *t*-statistics. ***, **, and * represent 1%, 5%, and 10% levels, respectively.

| | Independent Variable | | | | | | |
|---|---|---|---|---|---|---|---|
| Trading Variable | *Intercept* | $D_{Loss}$ | $D_{Mon}$ | $D_{Jan}$ | $D_{OG}$ | Adj.$R^2$ (%) | N |
| | | | ***Panel A. Order Imbalance*** | | | | |
| *OISVOL* | 0.2591*** | 0.0055* | 0.0084* | -0.0017 | 0.0076** | 1.94 | 38,248 |
| | (3.71) | (1.77) | (1.75) | (-0.24) | (2.22) | | |
| *OISNUM* | 0.5034*** | 0.0052* | 0.0057 | -0.0034 | 0.0086*** | 1.71 | 38,248 |
| | (98.46) | (1.65) | (1.13) | (-0.46) | (2.59) | | |
| | | | ***Panel B. Turnover*** | | | | |
| *TURNPER* | 0.0393*** | -0.0013** | -0.0055*** | 0.0017 | -0.0005 | 40.28 | 38,248 |
| | (44.51) | (-2.38) | (-6.37) | (1.36) | (-0.83) | | |
| *TURN* | 1.2705*** | -0.0369* | -0.1434*** | 0.2636*** | 0.0888*** | 18.24 | 38,248 |
| | (35.99) | (-1.69) | (-4.12) | (5.26) | (3.85) | | |
| | | | ***Panel C. Market Depth*** | | | | |
| *DEPTH* | 26.2476*** | -0.3195* | -0.2671 | -0.3834 | -0.3988** | 29.75 | 38,248 |
| | (6.32) | (-1.74) | (-0.94) | (-0.93) | (-1.96) | | |
| | | | ***Panel D. Spread*** | | | | |
| *DIF_ES* | -1.0098** | -0.0086 | 0.0684*** | 0.0593* | 0.0175 | 2.11 | 35,591 |
| | (-2.36) | (-0.60) | (3.07) | (1.83) | (1.10) | | |
| *DIF_QS* | -0.6494 | -0.0038 | 0.0470** | 0.0188 | 0.0298* | 2.01 | 35,591 |
| | (-1.54) | (-0.27) | (2.14) | (0.59) | (1.91) | | |
| | | | ***Panel E. Non-Institutional Investor Trading Volume*** | | | | |
| *NIVOL* | 0.9650*** | -0.0153*** | 0.0290*** | -0.0278*** | -0.0047 | 29.19 | 38,248 |
| | (15.14) | (-5.43) | (6.61) | (-4.39) | (-1.51) | | |

**Table IX. Effects of Football Game Outcomes on the Returns of NYSE stocks**

This table presents regression analyses of stock returns (in percentage) for NYSE-listed firms whose headquarters have the same first three-digit zip codes as the cities of NFL football teams. The results for the entire trading day and for the opening period (9:30-10:00) on the first trading day following the football game are presented in Panels A and B, respectively. $D_{Loss}$ equals one if the football team fails to cover the point spread (loses the game), and zero if it covers the point spread (wins the game). The control variables are dummy variables for Monday ($D_{Mon}$), January ($D_{Jan}$), and other U.S. major sports games ($D_{OG}$) as well as firm dummy variables. The coefficients on firm dummy variables are not presented in order to save space. Numbers in parentheses are *t*-statistics. ***, **, and * represent 1%, 5%, and 10% levels, respectively.

***Panel A. Daily Returns***

| | Independent Variable | | | | | | |
|---|---|---|---|---|---|---|---|
| Model | *Intercept* | $D_{Loss}$ | $D_{Mon}$ | $D_{Jan}$ | $D_{OG}$ | Adj.$R^2$ (%) | N |
| 1 | 0.2352 | -0.0121 | | | | 0.02 | 133,154 |
| | (1.28) | (-0.96) | | | | | |
| 2 | 0.4579** | -0.0155 | -0.2477*** | -0.1187*** | 0.0519*** | 0.17 | 133,154 |
| | (2.48) | (-1.23) | (-13.53) | (-4.01) | (3.74) | | |

***Panel B. Returns at the Market Open***

| | Independent Variable | | | | | | |
|---|---|---|---|---|---|---|---|
| Model | *Intercept* | $D_{Loss}$ | $D_{Mon}$ | $D_{Jan}$ | $D_{OG}$ | Adj.$R^2$ (%) | N |
| 1 | 0.0673 | -0.0035 | | | | 0.04 | 90,512 |
| | (1.17) | (-0.64) | | | | | |
| 2 | 0.1058* | -0.0034 | -0.0364*** | -0.0523*** | -0.0149** | 0.09 | 90,512 |
| | (1.82) | (-0.62) | (-4.57) | (-4.19) | (-2.52) | | |