Down and Out? Baseball Sentiments and Investor Behavior

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Abstract

We exploit an interesting setting of Korean professional baseball league to examine whether sports sentiment affect investor behavior at the stock and/or fund levels. Korean baseball league is different from the Major League Baseball in the U.S. in that teams are explicitly associated with *chaebol* conglomerates, generating a direct and cross-sectional variation in investor sentiment. Using daily fund flow data, we find evidence of significant outflows from funds that hold a large weight on a conglomerate member following the team's loss the previous day. This effect is the strongest among online retail funds, and this outflow does not appear to be driven by the investors' prescient response to poor future returns. At the stock level, we similarly document significant net selling of conglomerate member firms by retail investors following the team's loss. Using these cross-sectional variations, our paper uncovers strong evidence of behaviorally-motivated investment decisions driven by sports sentiment.

JEL Classifications: E52, E58, G14, G23

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1. Introduction

Sports sentiment can affect all aspects of people's lives; a tense World Cup qualifier match even led to a brief war between El Salvador and Honduras in July 1969. In a similar vein, losing in a crucial sports match such as a World Cup elimination game can significantly dampen the losing nation's aggregate stock returns, as found in Edmans, García, and Norli (2007). This forms an important part of the broader literature that examine the asset pricing implications of investor sentiment (e.g., Baker and Wurgler, 2006; Stambaugh, Yu, and Yuan, 2012; García, 2013; Da, Engelberg, and Gao, 2014). A dominant majority of the existing literature on investor sentiment, however, explores time series variations or cross-sectional variations at the market level; for example, Edmans, García, and Norli (2007) focus on aggregate stock returns at the national level. Given that there are numerous factors that affect a country's market on any given day, it is important to analyze whether a similar sports sentiment exists at a more micro, firm-level within a stock market. Moreover, which type of traders drive such sports-based sentiment effect is also yet to be determined. Our paper contributes to the literature by exploiting an interesting cross-sectional variation in sports-driven investor sentiment arising from the Korean baseball league.

It is well known that sports game results can affect the behavior of fans. Ample evidence in the psychology literature find that losing teams' fans express significantly higher degrees of boredom, anger, and resentment, as well as lower self-esteem (Wann, Dolan, MeGeorge, and Allision, 1994; Bernhardt, Dabbs Jr, Fielden, and Lutter, 1998; Bizman and Yinon, 2002; Kerr, Wilson, Nakamura, and Sudo, 2005). Such sentiment stems from so-called "balanced theory" (Heider, 1958; Cialdini, Borden, Thorne, Walker, Freeman, and Sloan, 1976), whereby fans identify their own well-being with that of their teams. It is thus no surprise that a loss can amplify negative sentiments; a narrow loss to Boston Bruins in Game 7 of Stanley Cup Final saw Vancouver Canucks fans rioting in the streets of Vancouver in June 2011. Since Edmans, García, and Norli (2007), a number of studies examine the asset pricing implications of these sports game results and find that a team's loss does translate into a subsequent underperformance in equity markets.

All major U.S. sports teams are linked to a local area. Though most baseball and American football teams are owned by well-known business figures, the link between a team's win or loss and stock returns of firms headquartered around the team's stadium is arguably weak.[1] For example, though Microsoft is based in Redwood, Washington, only a 20-minute drive away from the home stadium of Seattle Mariners, it is not particularly likely that a cognitive association would form between the Mariners' game result and investor perception of the Microsoft stock. In contrast, the Korean Baseball Organization (KBO) league, which has by far the highest attendance per game out of all major sports in Korea as shown in Figure 1, operate under a different structure. A team in the KBO league is associated both with a local area as well as a major *chaebol* conglomerate group. For example, the capital city of Seoul has two rival teams, LG Twins and Doosan Bears, both major conglomerates, while Samsung Lions is located in Daegu, the fourth largest city in Korea. If so, it is more natural to expect that the loss of Samsung Lions would generate sports-driven sentiment for Samsung affiliate companies' stocks, thereby generating an interesting cross-sectional variation in sports sentiment between different firms during the baseball season. This is in contrast to most other countries, where a popular sports team only has an association with a particular local area as in the cases of American football or baseball in the United States or soccer in most European and South American countries. This is also different from an empirical examination of sports teams that have been listed in various stock exchanges, where poor performance could have material cash flow implications in the form of lost ticket sales and marketing revenue in addition to investor sentiment.

FIGURE 1 HERE

By engaging in a more micro-level, cross-sectional analysis of sports sentiment, we are also able to obtain a more direct measure of investor response compared to the majority of the existing studies that examine only the aggregated stock returns. However, for a trade to occur, there has to be a buyer for every seller, and it is thus difficult to discern how a particular group of investors react to sports sentiment. In contrast, since the Korea Exchange (KRX) publishes aggregated buy and sell order volumes of each major

[1] An exception, however, is Chang, Chen, Chou, and Lin (2012), who find lower next-day returns among firms headquartered in a local area with an NFL game loss.

trader group, e.g., retail, institutional, and foreign, for each firm at every market close, we are able to directly measure how individual investors in Samsung member firms, for example, react to the loss of Samsung Lions the previous night. Similarly, by obtaining daily fund flow and monthly fund holding data, we are also able to uncover whether fund share classes that cater to retail investors suffer from outflows when they overweight a conglomerate member firm's stock with a recent team loss. Thus, our data and the empirical setting enable us to delineate retail investor responses in a more direct manner.

Using the data on Korean stock market and domestic equity funds between 2013 and 2018, we first determine whether sports-driven sentiment effect manifests itself as stock returns. In line with the previous literature, we find that *chaebol* affiliate firms whose baseball team has been doing poorly over the past week subsequently experience poor returns. The sentiment effect is statistically significant only for the cases of losses but not wins, similar to the patterns documented in Edmans, García, and Norli (2007). In terms of economic magnitude, we find that a team experiencing a week of losing streak subsequently experiences a cumulative fall in return of around 0.25% over a five-day period. This is not as large as the next-day fall in returns in major soccer nations following a loss at the World Cup elimination stage as documented in Edmans, García, and Norli (2007), but still a substantial figure, nevertheless.

We then explore whether there exists a particular group of traders that drive this pattern. To this end, we examine the normalized order imbalance of individual, institutional, and foreign investors trading in these *chaebol* firms. We find that the selling pressure following a team's losses stem mainly from individual investors. In contrast, we find little evidence of such aggregate selling pressure for the cases of institutional and foreign investors. Thus, it appears that individual investors exhibit the highest degree of susceptibility to sports-sentiment-driven trading behavior.

However, aggregate net order imbalances of each trader group, though indicative, are nevertheless at best a noisy measure of investor response; for every buyer, there ought to be a seller, and it is possible that some institutional investors exert sentiment-driven selling pressure, which are in turn borne out by other institutional investors. To address this problem, we exploit a related setting of open-end mutual fund flows. Mutual fund flows are cleaner measures of aggregate investor response, because instead of trading

with each other, investors submit subscription and redemption orders to the fund management company. To this end, we examine whether investors, on the whole, pull their money out of a fund that holds much weight on a *chaebol* affiliate firm whose baseball team's recent performance has been poor. Given that the top 10 holdings of a fund are always highly publicly visible, our main measure of investor sentiment is whether a fund holds shares of a conglomerate member within its top 10 holdings whose baseball team won or lost the previous night.

Following a team's poor performance over the past week, we find a significant outflow from domestic equity funds that hold one or more of the conglomerate's constituent members within its top 10 holdings. Once again, the sentiment effect is concentrated mainly for losses rather than wins. In economic terms, we find that a week of losing streak is associated with extra investor outflow of around 0.05% over the 5-day period. Though the economic magnitude may appear small at first, given that we employ a two-way interacted fixed effect of fund-type-by-time, our results uncover the existence of extra outflows even when comparing between funds with similar mandates during the same trading day, which is a significant finding. In contrast, we do not observe a similarly significant response after a team's win, in line with Edmans, García, and Norli (2007) and Chang, Chen, Chou, and Lin (2012). Therefore, selling pressure appears to exist both at the individual stock as well as at mutual fund level, whereby a fund that places large weights on the stocks of losing baseball team's affiliate firms witnesses greater outflows.

We then engage in a further set of analyses to discern whether this impact likely emanates from investor response to sports sentiment. First, we examine whether this outflow is stronger after important games. We find evidence of stronger next-day outflow, with marginal statistical significance at the 10% level, when a team at the top of the league loses their position following the game. Moreover, the estimated economic magnitude of the next-day outflow is also stronger after the loss during the post-season playoffs and the Korean Series, the Korean equivalent of the MLB World Series. Thus, the outflow patterns do appear to be driven, at least in part, by the importance of the game, yielding further support to our notion that these outflows reflect sports-driven sentiment.

Second, we engage in a subsample analysis of online-and-offline retail, online-only retail, and institutional share classes. We focus on online-only retail share classes, as these are the preferred means of fund trading among the main age group for baseball fans, namely those in their 20s to 40s. We find that online-only retail share classes—and retail classes in more general—exhibit the highest economic magnitude of around 0.02%. In contrast, we do not find a significant change in fund flows in response to baseball game results among institutional classes, further suggesting that the observed flow patterns appear to be driven by those more susceptible to sentiment investing. Thus, the documented patterns of sports-driven investor behavior at the stock level also appears to hold firm at the mutual fund level.

We engage in a number of robustness checks to rule out possible alternative stories. First, we check whether such selling patterns are *ex post* justified by engaging in a calendar-time portfolio analysis of winning and losing teams' constituent member stocks over the next 5- or 20-day horizon. This analysis intends to capture whether the individual investors are "smart money" investors (e.g., Gruber, 1999; Zheng, 1999; Sapp and Tiwari, 2005). There is virtually no difference in the *ex post* performance of winning and losing teams' member stocks, suggesting that the significant selling of these stocks after the baseball game loss do not appear to be driven by a rational anticipation of future stock market movement. Second, we check the possibility that this selling behavior of individual investors arises from a rational, cash-flow-based view, whereby investors are wary of the team's losses having a bad corporate image and becoming a marketing liability. However, if this alternative story is to be true, the effect ought to be more prominent in consumer-oriented firms that sell products directly to the consumers rather than business-oriented firms. We find no such evidence, and the selling behavior is pervasive across both business- as well as consumer-oriented firms, casting doubt on this alternative story.

We contribute to the literature in several ways. First, we contribute to the large literature that examines asset pricing implications of behavioral finance, ranging from a macroeconomic perspective (e.g., Barker and Wurgler, 2007; Da, Engelberg, and Gao, 2014) to weather (Hirshleifer, Shumway, 2003; Kamstra, Kramer, and Levi, 2003) and sports (Edmans, Garcia, and Norli, 2007). Our contribution here is twofold. First, by exploiting a natural setting that generates direct cross-sectional variation in sports

sentiment between different firms, we are able to uncover the asset pricing implications of sports-driven sentiment while controlling for a wider range of firm-level characteristics and maintaining a strong association between the firm and the sports team. In addition, our order imbalance data by trader group and flows into and out of different types of share classes enable us to uncover that individual investors are the primary drivers of these sentiment-driven trading. Second, we contribute to the literature linking fund flows and investor sentiment (e.g., Frazzini and Lamont, 2008; Ben-Raphael, Kandel, and Wohl, 2012; Kumar, Niessen-Ruenzi, and Spalt, 2015) by examining flows into and out of each fund class at the daily level. In addition to existing evidence that suggests investor flows being affected by non-performance factors such as fund manager's surname (Kumar, Niessen-Ruenzi, and Spalt, 2015)), we uncover clear evidence of sports-sentiment-driven flows in mutual funds.

2. Data and variable construction

We first outline how the Korean baseball league operates. The main Korean baseball league is the Korean Baseball Organization (KBO) league, which has 10 teams participating as of 2018. The league's regular season, similar to the U.S., runs from late March to October. Regular season baseball games are held from Tuesday to Sunday of each week. On weekdays, the games begin at 6.30pm, and on weekends, the games begin either at 2pm or 5pm. Each team plays 144 games in total during the regular season, meeting each opponent for 8 games at home and on the road, respectively. Then, the top teams progress onto the playoff stage, with the teams ranked fourth and fifth playing the wild card decider, whose winner play the third-ranked team in the semi-playoff in a five-game decider, whose winner then plays the second-ranked team in the playoff in a best-of-seven-games format. The Korean Series wraps up the season by pitting the playoff winner against the top-ranked team in a seven-game decider. All teams are tied to a local area, with Seoul having three teams in total, namely LG Twins, Doosan Bears, and Kiwoom Heroes. Other cities with a baseball team are major cities in Korea, namely Busan (Lotte Giants), Daegu (Samsung Lions), Incheon (SK Wyverns), Gwangju (KIA Tigers), Daejeon (Hanwha Eagles), Changwon (NC Dinos),

and Suwon (KT Wiz). All but one team are owned by a major conglomerate or standalone firm in Korea.[2]

We obtain the KBO game results directly from their official webpage, which lists the final score of each game, as well as reasons for delay, if any. For the main analysis, we use both the regular season and postseason game results.[3] Our main variable of interest is the number of wins or losses that a team experienced over the past week. We prefer this measure to a day-by-day measure of win or loss given the frequent nature of baseball games. Unlike American football or soccer games, which are played at most once or twice a week, baseball games are different in that there are five to six games occurring every week. A team plays the opponent for a block of either two or three games over consecutive days, e.g., Tuesday to Thursday, and in many instances, fans expect to lose a particular game and are concerned more about the overall "block" results, for example when their rookie starting pitcher is being pitted against the opponent's top "ace" pitcher. Thus, for our main analysis, we focus on the rolling number of wins and losses over the past week.[4]

Furthermore, given that most baseball teams are owned not by individual firms but by *chaebol* conglomerates, it is important to match a team's result with the *chaebol*'s constituent members. We use the latest annual data published by Korean Fair Trade Commission with regards to a *chaebol* conglomerate's membership to identify all affiliate firms. We then obtain each firm's stock-level information, including returns and order imbalances. Korea Exchange (KRX) publishes every stock's total amount of buys and sells (both in terms of number of shares as well as total values) by each trader group, namely individuals, institutions, and foreigners. This allows us to calculate the normalized order imbalance (OIM) for each group at each trading day *t*, defined as follows:

$$OIM_t = \frac{(Purchase_t - Sales_t)}{(Purchase_t + Sales_t)}. \quad (1)$$

[2] Kiwoom Heroes is an exception in this regard. It is a privately-owned team, who has a sponsorship deal with a major Korean securities firm, Kiwoom Securities. Results are consistent regardless of whether they are excluded from the analysis.

[3] Before the season begins, there are around two weeks of "pre-season games." However, these games are excluded as baseball fans do not exhibit much interest in these games.

[4] We check in untabulated analysis other horizons for summing up baseball wins and losses, as well as running regressions using only the previous nights' win or loss. Results are mostly consistent, with marginally weaker statistical significance.

For the empirical analysis on stock returns, we use the set of controls similar to Brennan, Chordia, and Subrahmanyam (1998), namely the latest price level, log size, book-to-market, log dollar volume, and log dividend yield. These measures are constructed using data from FnGuide's DataGuide platform.

In addition to the data on stocks, we use fund flows as additional measure of investor sentiment. To this end, we obtain daily fund flow and holdings data from KG Zeroin, a major fund rating firm in Korea, for all open-end active domestic equity funds in Korea between 2013 and 2018. We distinguish active funds from passive funds using KG Zeroin's own classification code. The main variable of interest is the total number of baseball game wins (or losses) that a fund's top 10 holdings experienced over the previous week. We focus on the top 10 holdings as all Korean funds disclose precisely this measure on their fund webpage at the end of each trading day, implying that these are highly visible to all groups of investors. It would be difficult to surmise that investors' flows would differ on the basis of fund holdings that are not publicly disclosed, so a fund's top 10 holding is the more natural measure in this regard. Our sample of funds cover a dominant majority of the Korean equity market, a distinct advantage over other datasets used in the U.S. such as those provided by TrimTabs (e.g., Edelen and Warner, 2001), which only cover around 20% of the U.S. equity funds' total assets under management.

We also calculate holding-level measures of risk factors. Specifically, using the month-end fund holding data, we calculate at each month-end the latest holding-weighted-average of Fama-French three-factors (1992) of the fund's constituent securities. Security-level market, size, and book-to-market factor exposures are calculated using the complete universe of Korean stocks at each month-end, using the identical formation methods as in Fama and French (1992) over a rolling 250-day window. In addition, we compute the standard controls in the literature on fund flows such as expense ratio, management firm size, and the TNA-percentage of share classes with a front or rear load fee. Table 2 provides the summary statistics of all main variables used in our paper, with Panels A and B providing the summary statistics for our stock- and fund share class-level analyses, respectively.

TABLE 2 HERE

3. Baseball Sentiment and the Stock Market

3.1. Are stock returns affected by baseball sentiment?

We first estimate whether the investors' sports-driven sentiment manifests itself in stock returns at the aggregate level, as found in previous studies in the literature. To this end, we run pooled panel regressions of daily stock returns on sentiment variables and other controls. In particular, given that the baseball games finish late at night after the market close of the same day, we focus our attention on open-to-close returns of the next available trading day. For conglomerate affiliate firms, our main variable of interest is the number of losses and wins that the baseball team experienced during the previous 5-day rolling horizon. If the sports sentiment manifests itself into stock returns of each member team, we expect one or both of this measure to have a significant impact on stock returns. In particular, given the findings in the literature, we expect the previous 5-day number of losses to have a significantly negative impact on the stock returns. Our controls are identical to those in Brennan, Chordia, and Subrahmanyam (1998), namely: price level, log size, book-to-market, log dollar volume, and log dividend yield. In addition, we control for returns over the following non-overlapping horizons: -1, [-5:-2], [-10:-6], and [-20:-11]. We run pooled panel regressions with standard errors clustered by both firm and day,[5] and we further include either broad- or narrow-defined industry fixed effect defined according to the Korean Standard Industry Classification (KSIC), which are more or less equivalent to SIC 2-digit and 3-digit controls, respectively. In addition, we include day fixed effect. Table 3 presents our results.

TABLE 3 HERE

Column (1) of Table 3 presents our results without industry fixed effect, while columns (2) and (3) present results with either broad or narrow industry fixed effect. Regardless of how we capture the industry fixed effect, we find that the next-day open-to-close returns are significantly negatively affected when a member firm's baseball team loses the game. Our point estimate on the previous 5-day number of losses of -0.016 to -0.017 is remarkably similar regardless of how industry fixed effect is defined, and

[5] Instead of including clustering by date, we run Fama-MacBeth (1973) regressions in untabulated analysis. We find results to be broadly consistent, albeit with marginally weaker significance.

implies that, when a team has a losing streak of five straight games, its cumulative impact on the return over the same 5-day horizon is around -0.25%, which is of a sizeable economic magnitude. In contrast, the number of wins over the previous 5 days have much weaker statistical significance, in line with the previous findings in the literature (e.g., Edmans, García, and Norli, 2007). In untabulated analysis, we also run similar regressions using the previous night's game result, i.e., whether the baseball team won or lost the previous night and find that the return regression results are consistent but with somewhat reduced economic and statistical significance. This is different from previous studies that examine investor sentiment associated with soccer or American football that document more immediate market reaction, but we surmise that this is mainly due to the relatively frequent nature of baseball games, which occur six times a week for a total of 144 games during a regular season. If so, we surmise that sports fans are less likely to be concerned about the win or loss of a single game; instead, the effect is likely to be much more pronounced if a team is exhibiting a recent array of wins or losses.

3.2. Analysis of order flow imbalance: Who drives the sentiment-based selling?

Having documented the evidence suggestive of significant selling driven by sports sentiment in the stock market, we now turn to the issue of which type of investors drive such phenomenon. Previous studies on investor sentiment (e.g., Grinblatt and Keloharju, 2001) document that individual investors are likely to be more prone to such sentiment-based selling. We examine whether this is the case using a simple regression framework of normalized order imbalance. As explained earlier, at each market close, KRX publishes total amount of buys and sells for each stock by investor category, namely foreigners, individuals, and institutions. We construct normalized order imbalance as the difference between buys and sells of each trader group divided by the sum of buys and sells during the same day. A similar measure has been used in numerous previous studies (e.g., Chordia, Roll, and Subrahmanyam, 2002) to investigate the impact of trading imbalance. If, as we posit, individual investors are primarily susceptible to sports sentiment, we expect to see significant net selling on the part of individual investors in conglomerate affiliate firms following baseball game losses. To this end, we regress normalized order imbalance of each group on the

previous 5-day number of baseball wins and losses, along with lagged order imbalance as well as broad industry and day fixed effects. Once again, we use standard errors that are robust to heteroscedasticity and autocorrelation and two-way clustered by firm and day. Table 4 presents our results.

TABLE 4 HERE

Table 4 reveals that individual investors are primarily responsible for the significant selling of conglomerate member firms' stocks following the teams' recent streak of losses. The previous 5-day number of baseball losses has a significantly negative impact on the next-day individual investor order imbalance, with statistical significance at the 1% level and *t*-statistic exceeding 3. In contrast, we do not observe such significant imbalances in order flow among institutional or foreign investors following the baseball game losses, suggesting that the sentiment-driven selling is mainly confined to individual investors. Taken together, our results in Table 4 identify individual investors to be the main driver of significant selling of a conglomerate affiliate firm's stock that occurs following their baseball team's losses. However, given that there has to be both a buyer *and* a seller for a trade to occur, we now turn to a more direct setting of investor response, namely flows in and out of open-end mutual funds.

4. Baseball Sentiment and Fund Flows

4.1. Do baseball game losses result in substantial outflows?

The previous section has established that conglomerate members' stock returns are significantly depressed when their baseball teams' recent performances have been poor, and that this negative return appears to be driven mainly by individual investors' selling pressure. We now examine whether a similar sentiment-based flow response exists in open-end mutual funds. Unlike in stock markets, where trades occur *between* investors, we directly observe the extent of flows in and out of mutual funds, allowing us to discern with greater clarity how investors respond to baseball game losses.

To this end, we construct a following regression model. First, we construct the daily net flow of each fund share class, defined as the total net flow at day t divided by its total net assets (TNA) at $t-1$. Our main variable of interest is the fund's top 10 holdings, which are disclosed to the investors at the end

of every market close. It would not be reasonable to assume that investors respond to fund holdings that they cannot observe publicly, and thus the list of top 10 holdings is the most natural measure in this regard. We then compute the total numbers of wins and losses that the conglomerate member firms within the fund's latest top 10 holding have experienced over the previous 5-day window. In other words, if a fund holds Samsung Electronics and LG Electronics within its top 10 holdings, and if both teams have lost 3 times and 4 times within the previous 5-day window, respectively, then our measure of previous 5-day number of losses is counted as 7. Given that this disclosed portfolio holding has a significant impact on the fund investors' flow decisions (e.g., Musto, 1999; Solomon, Soltes, and Sosyura, 2014), we expect that any sports-sentiment-driven impact would manifest itself through investors moving money out of funds that place a large weight on conglomerate member firms with poor recent baseball team performances.

In addition to the top 10 holdings' previous 5-day number of wins and losses, we include a large number of controls. First, we control for fund flow and return over four non-overlapping horizons, more specifically days -1, -2, [-5:-3], and [-10:-6],[6] as mutual fund flow is known to exhibit high degrees of auto-correlation (Edelen and Warner, 2001). We further control for the latest month-end estimate of portfolio holdings' weighted-average Fama-French three-factor exposures, namely MKT, SMB, and HML, out of concern that conglomerate member firms tend to be large, growth firms. We include the standard set of fund characteristics commonly used in the literature, namely fund size (defined as the log of fund total net assets at the latest month end), log management firm size, fund age, expense ratio, and dummy variables indicating whether the share class charges front or rear load fees. The regression is at the fund share class-day level, and we include fund-type-by-day fixed effects, using KG Zeroin's own classification of fund types, which are broadly comparable to Lipper's classification of U.S. mutual funds. The inclusion of this two-way interacted fixed effects is significant in that we are comparing funds with similar mandates on a given day, which allows us to control for any unobserved heterogeneity driven at a particular day for a particular fund type. Table 5 presents our results.

[6] Results are consistent when we include longer horizons such as [-20:-11] and/or [-40:-21].

TABLE 5 HERE

Once again, we find that investors pull money out of funds that place a large weight on firms whose baseball teams' recent performance has been poor. In terms of economic magnitude, a five-day losing streak of Samsung Lions, for example, depresses investor flows of fund that hold a Samsung member firm within its top 10 holding by -0.05% over a five-day horizon. In contrast, a fund does not experience a similar inflow when its top 10 holding's baseball team has had stellar performance over the past week, suggesting that there is asymmetry, similar to the findings of Edmans, García, and Norli (2007). Thus, it appears that the effect of sports sentiment is largely asymmetric, with investors pulling money out of stocks and mutual funds following poor baseball performance, but we do not observe a corresponding increase in investor flows following a run of winning streak. As in Edmans, García, and Norli (2007), we believe this result to be consistent with previous consensus in the psychology literature, whereby strong psychological effect of a sports team, including incidences of heart attacks, a spike in crime rates, and even suicides, is mainly confined to losses but not to wins. This is also in line with Kahneman and Tversky's (1979; 1992) prospect theory, whereby investors' utility is more severely affected by losses compared to wins. To the extent that investors personally identify their own well-being with that of the sports team that they follow, the observed patterns are consistent with the previous literature on behavioral finance. However, the fact that sports sentiment remains strong both at the stock and at the fund levels, the latter of which holds even after the inclusion of fund-type-by-day fixed effects, is a strong indication that the sentiment-driven selling documented in previous studies appears not to be related to any unobserved heterogeneity at the national or day level. In fact, the fact that our results echo their findings at a more granular firm level throughout the regular baseball season implies that sports-sentiment-driven selling is pervasive and not confined to major international sporting events.

4.2. Who drives sentiment-based outflows in mutual funds?

Another advantage of exploiting the setting of mutual fund flows is that different share classes cater to different types of investor clientele. In Korea, there are different type of fund share classes for

different types of investors. In addition to the traditional institutional-retail class split, retail share classes are further split into those that can exclusively be purchased online, which we refer to as online only retail, and those that can also be obtained through a brokerage firm or a bank's marketing channel, which we refer to as online-offline hybrids. Any fund share class with a type code that ends in "e" are online-only retail classes. However, as shown in Figure 2, the major demographic age group of the baseball fan base is centered around those in their 20s to 40s, who also happen to be the major investor base of the online-only retail classes due to their savvy adaptability to new means of internet-based technology. Thus, we expect that any sports-sentiment-driven flows would manifest primarily in this fund share class subsample. To this end, we re-estimate the flow regressions in Table 5 for each of the following subsamples: (i) online-only retail classes, (ii) online-offline hybrid retail classes, (iii) all retail classes, which is the sum of (i) and (ii), and (iv) institutional classes. Table 6 presents our results.

TABLE 6 HERE

As expected, we find that the strongest statistical significance of sentiment-driven outflows following poor recent baseball performance stems primarily from online-only retail classes, with a p-value close to 1%. In contrast, for online-offline hybrid retail or institutional classes, we do not observe any evidence of significant selling even when a fund holds a conglomerate member firm with poor baseball performance within its top 10 holdings. Thus, as in Table 4, we confirm that retail investors, particularly young investors that utilize online-only share classes, are the primary drivers of this sentiment-driven fund flows, suggesting that our findings are primarily a retail investor phenomenon. This is in line with the prior literature that find institutional investors to be less prone to sentiment-driven irrationality compared to retail investors (e.g., Gruber, 1996). For this subsample of investors, we also observe a more immediate reaction to baseball game result, with the previous night's game result translating into an immediate next-day fund outflow, as shown in Panel B.

Taken together, our results in Sections 3 and 4 strongly indicate that retail investors, particularly those belonging to a relatively younger age group that are the main fan base of baseball teams, are the main drivers of sport-sentiment-driven selling at the stock level as well as outflows at the mutual fund

level. In this respect, we complement the existing studies of sports sentiment by detailing the particular type of traders that are susceptible to sports sentiment at the cross-sectional firm level generated by baseball game results.

5. Discussion

5.1. Is there a "smart money" effect?

In previous sections, we have interpreted subsequent selling or outflows associated with baseball game losses as being consistent with sentiment-driven. However, a similar phenomenon could also be consistent with rationality on the part of individual investors if there are plausible reasons to believe that baseball game losses are mere proxies of conglomerate member firms' future cash flows. For example, well-performing conglomerates are likely to have better cash flow prospects—leading to a higher stock return—while their ability to spend more in baseball teams could lead to better overall performance. For example, in Major League Baseball, the team with the most World Series wins by far, namely New York Yankees (who have won 27 out of their 40 World Series appearances), has consistently been one of the top teams in terms of payroll. Similarly, fund managers that overweight conglomerate members with poor baseball performance, according to this logic, could be indicative of exhibiting inferior stock-picking ability. To this end, we first distinguish whether fund outflows documented in Section 4 are *ex post* justified by under-performance over a longer horizon. Specifically, we construct a zero-cost return portfolio of our sample of mutual funds, purchasing a fund that includes a winning team's stock in its top 10 holding and shorting a fund whose top 10 holding includes a losing team's stock, holding the position for the next 5 or 20 trading days. Though it is not possible to short sell open-end mutual funds in practice, this exercise is intended to identify whether there is statistically significant difference in the subsequent performance of fund managers that overweight winning and losing teams' member stocks over a longer horizon.[7] We do so both for the full sample as well as for each quintile of funds based on their previous one-year return performance. We then calculate this calendar-time portfolio's alphas over Fama-French (1992) three-factor

[7] In untabulated analysis, we perform a similar test directly at the stock level and find consistent results.

model, although the results are consistent regardless of factor model specifications, namely Carhart (1997) four-factor, Fama-French (2015) five-factor, and five-factor-plus-momentum models, which we confirm to be the case in untabulated analysis. Table 7 presents our results.

TABLE 7 HERE

Both for the full sample and for each past performance quintile, we find the alphas to be lacking in statistical significance. The economic magnitude of daily alphas is also practically zero, suggesting that funds that hold winning teams' stocks in their top 10 holding are indistinguishable from those that place a large weight on losing teams' stocks, suggesting that, at least from an *ex post* perspective, there is no good reason to be engaging in a significant selling of the latter group of funds. Though this type of calendar-time portfolio tests tend to exhibit low power, as highlighted by Loughran and Ritter (2000), the fact that alphas are virtually zero both in terms of economic *as well as* statistical significance is nevertheless strongly suggestive of the fact that investors' selling behavior cannot easily be justified through fund managers' *ex post* performance, casting strong doubt on any alternative explanation based on "smart money" effect.

5.2. Is there a sports marketing effect?

Another plausible explanation for the observed investor outflows is that sports results could have a tangible impact on the member firms' cash flows through the sports marketing channel. According to Geng, Burton, and Blakemore (2002), firms provide sponsorships to professional sports teams to gain a positive image from consumers, which in turn can significantly affect consumers' purchase intentions (e.g., Koronios et al., 2016). The fame of professional sports teams can thus have a significant impact on its sponsor firms' sales revenue, which could plausibly explain why many consumer product firms spend hefty sums of money at major sporting events such as Super Bowl half-time commercials. However, this type of sports marketing only works well when the team's performance is excellent to begin with; after all, it would be difficult to expect fans to drive up sales when the sponsoring team is on a serious losing streak. According to this line of alternative story, poor recent performance of a baseball team in turn reduces the effectiveness of its members' sports-based marketing drive, thereby depressing revenue prospects. If this

line of story were to be true, however, then this effect ought to be concentrated among consumer product firms or firms that sell directly to consumers. In contrast, those engaged in business-to-business industries are less likely to be affected by such sports marketing. Thus, the extent of outflows ought to be severely concentrated only among funds that place a large weight on losing team's consumer-oriented firms. To this end, we construct an indicator variable for business-oriented firms. Specifically, we gather the data on firms' sales by segment, and we manually identify each segment as business-to-business or business-to-consumer. Then, a business-oriented firm is defined as a firm with recorded sales only in the business-to-business segments. Then, we re-run the flow regressions in Table 5 with the top 10 holdings' previous 5-day number of baseball game wins and losses both interacted with the business-oriented firm dummy. A positive interaction term on the number of losses and business-oriented firm dummy would be consistent with the sports marketing-based explanation, while an insignificant or negative interaction term would cast doubt. Table 8 presents our results.

TABLE 8 HERE

We find that the interaction term between the number of baseball game wins (or losses) within a fund's top 10 holding over the previous 5-day horizon and the business-oriented firm dummy is largely insignificant. In other words, sentiment-driven outflows appear to be evident in funds that place a large weight on losing conglomerate team's stocks regardless of whether they hold business- or consumer-oriented firms. This casts doubt on any explanation based on sports marketing, given that higher revenues resulting from sports marketing are unlikely to occur in business-to-business transactions.

5.3. Do some games elicit more pronounced investor response?

If the observed patterns are consistent with sports-driven sentiment, then it would be reasonable to expect that the extent of investor response would be greater following the loss of an important game. For example, suppose that Samsung Lions have clinched the regular season title with six games to spare. A loss during these remaining "unimportant" games is unlikely to generate sizeable changes in investor sentiment. On the other hand, suppose that a loss results in a team losing its playoff wildcard spot from

the fifth to the sixth position. Such a loss would be deemed much more important in the fans' eyes, and a loss would in turn elicit greater response. We therefore identify a particular set of games that are likely to elicit more pronounced investor sentiment, namely wins or losses during the regular season that result in a team gaining or losing its current rank. From a baseball fan's standpoint, this type of games significantly upend the *status quo*, or reference point to borrow the terminology of prospect theory. As such, is likely to have a significant impact on their sentiment. Thus, we create two indicator variables that capture such type of wins and losses, and we re-run flow regressions in Table 5, with these two "important game" variables added to the original set of sentiment variables. Table 9 presents our results.[8]

TABLE 9 HERE

As expected, we find that the investor response to the baseball game loss of a fund's top 10 holding member firm is much more prominent when it results in the team's loss of current rank. In fact, our estimates in Table 9 implies that a sizeable bulk of the outflow response documented in Table 5 appears to be driven mainly around the team's rank changes. In contrast, investor response to a loss that does not affect the team's current rank appears to be much more subdued. Thus, baseball fans' sentiment-driven outflows appear to be driven not by the results of each and every game, but when the team loses its current position in the league, a finding in line with the predictions of prospect theory.

Secondly, we explore whether post-season games elicit greater investor response. In particular, KBO games are different from Major League Baseball in the U.S. in that, during the post-season, only one game is played on any given night, with the baseball followers' attention glued to a single national-level game. In contrast, up to four division series games and two championship series games can occur concurrently during a given post-season game night, diverting baseball spectators' attention at the national level. Thus, we believe that a loss during such an important game would garner more pronounced investor response. We thus interact our main measures of top 10 holdings' previous 5-day wins and losses with a

[8] Because we focus on rank changes during the regular season, we focus on all fund share class-day observations during the regular season, resulting in a smaller set of sample observations.

dummy variable indicating the post-season dates and re-estimate the flow regressions in Table 5. Table 10 presents our results.

TABLE 10 HERE

As expected, in both instances, we find that the extent of investor outflows from a fund that places a large weight on a losing team's member stock is much greater during the post-season, with a tenfold increase in economic significance and statistical significance at the 5% level. In other words, whereas a loss during a baseball season elicits investor outflows even under normal circumstances, its extent becomes even more pronounced when the member firm's team loses a post-season game.

We also check whether the margin of the defeat matters. There is no particular reason to expect *a priori* whether the investors would react more strongly to narrow margin or wide margin defeats. On the one hand, losing a close game may leave a deeper sense of regret on investors. On the other hand, a team's horrendous performance resulting in a wide margin defeat may instill a sense of anger and resignation due to the sheer scale of the defeat. It is also possible that the margin of the defeat may not matter much altogether. To this end, we identify all games whose final score was decided by one run as narrow margin defeats, and those with a margin of five or more runs as wide margin defeats, and check whether the extent of investor response differs. Table 11 presents our results.

TABLE 11 HERE

Evidence in Table 11 suggests that investor outflows are particularly sensitive to narrow losses. This could be explained by the fact that, in many of the wide margin losses, investors may have expected the game result to be a foregone conclusion *ex ante*, perhaps because their team is playing against a much more dominant opposition or a "hot" starting pitcher. In contrast, losing a closely contested game could instill a greater sense of anger and regret, which could in turn translate into a more pronounced investor response in the form of fund outflows. Overall, our evidence suggests that the nature of the game matters for subsequent fund flows, with a change in a team's rank or a loss during a post-season playoff resulting in a more pronounced investor response.

6. Conclusion

In this paper, we complement the existing studies on investor sentiment using a unique setting of Korean baseball league, which generates a direct and interesting cross-sectional variation in sports sentiment at the individual firm level during its regular season. In contrast to the many of the previous literature on investor sentiment, where the variation in sentiment is mainly time series driven, we exploit this cross-sectional variation to demonstrate sizeable and significant existence of sports sentiment both at the stock and at the fund levels. At the stock level, we document that a conglomerate member firm's next-day return is depressed following a baseball game loss. At the fund level, we document a similar outflow away from funds that place a large weight on these member firms. In both instances, we document that such sentiment-driven selling or outflow appears to be primarily a retail phenomenon, with individual investors, particularly those that are in the main age group for baseball fan base and trade actively online, driving such sentiment-based selling at the stock or fund level. Further analyses show that our observed patterns are unlikely to be accounted for by a rational explanation based on a confounding cash flow prospect or sports marketing story, and we further document that the extent of investor response is greater following losses of important games, such as a post-season game or a loss that results in a team losing its current rank in the baseball league.

The main contribution of our paper lies in the fact that we are able to document a particular trader group, namely domestic individuals, to be the main driver of such sports-sentiment-driven investing in stocks and mutual funds. Moreover, by engaging in an extensive analysis of fund flows in addition to the examination of stock returns and order imbalances, we are able to uncover with greater accuracy how the investors respond to game losses. The fact that individual investors can drive up temporary imbalances in stock returns and fund flows reiterates the importance of examining investor sentiment in enhancing our understanding of asset pricing in general; even a seemingly innocuous factor such as losing a baseball game can significantly affect individuals' perception of a firm or a fund's future prospects.

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Table 1. Fan Base of Professional Sports in Korea

This table presents the average number of spectators per game for each of the major professional sports in Korea between 2013 and 2018. The data is published from Korea's Ministry of Culture, Sports, and Tourism.

		2013	2014	2015	2016	2017	2018
Baseball	No. of Game	593	591	736	720	720	720
	Average spectators per game	11,373	11,429	10,357	11,583	11,668	11,668
Soccer	No. of Game	266	229	228	228	228	228
	Average spectators per game	7,656	8,115	7,720	7,854	6,502	6,502
Male Basketball	No. of Game	300	301	292	291	291	291
	Average spectators per game	4,092	4,458	3,953	3,543	3,188	3,188
Female basketball	No. of Game	113	112	111	112	112	112
	Average spectators per game	1,237	1,417	1,480	1,425	1,097	1,097
Volleyball	No. of Game	210	227	227	229	229	229
	Average spectators per game	1,525	1,967	2,311	2,336	2,425	2,425

Table 2. Summary Statistics

Panel A of this table presents summary statistics for our analysis at the stock-day level. Our sample consists of XXX firms in Korean stock market between 2013 and 2018. The observation is at the stock-day level. Excess returns are calculated over the risk free rate, which is the rate on 1-year monetary stabilization bond issued by the Bank of Korea. 5-day number of losses and wins is the number of baseball game wins or losses that the firm's baseball team, if any, experienced during the previous rolling 5-day window. All other controls are computed in the analogous manner to Brennan, Chordia, and Subrahmanyam (1998). Panel B then presents summary statistics at the fund level. Our initial sample consists of KG Zeroin's survivorship-bias-free open-end fund universe between 2000 and 2018. However, daily flow and holdings data are available only between 2012 and 2018. We calculate the weighted-average three-factor coefficient of each equity fund's holding-level securities. MKT, SMB, and HML are monthly exposure of each stock to Fama-French three factors, calculated in the analogous manner to Fama and French (1992) using the universe of Korean stocks for a rolling one-year window at each month-end. We calculate daily fund flow as computed by daily net fund flow divided by the previous market close TNA. Daily return is fund class's return. Fund TNA is a previous month-end total net asset of each fund share class. Management firm TNA is a previous month-end total net asset of fund management firm. Expense ratio is an annualized figure in percentage terms. Share of front and rear load classes are computed using the TNA of all share classes with a front and rear load fee within the fund, respectively. Fund age is the age of the oldest share class.

Panel A. Stock-Level Summary Statistics

	Obs.	Mean	St. Dev.	Q1	Median	Q3
Excess return (open-to-close, %)	2,685,651	0.222	2.813	-1.230	0.199	1.698
Excess return (close-to-close, %)	2,685,651	0.026	2.666	-1.326	-0.117	1.129
5-day number of losses	2,685,651	0.040	0.302	0.000	0.000	0.000
5-day number of wins	2,685,651	0.039	0.294	0.000	0.000	0.000
Book-to-market	2,685,651	1.029	0.846	0.436	0.819	1.363
Log dollar volume	2,685,651	20.24	2.035	18.90	20.24	21.61
Log size	2,685,651	25.68	1.401	24.72	25.44	26.36
Log dividend yield	2,685,651	0.492	0.553	0.000	0.322	0.920
RET [-5 : -2]	2,685,651	0.001	0.057	-0.028	-0.002	0.026
RET [-10 : -6]	2,685,651	0.002	0.064	-0.032	-0.002	0.029
RET [-20 : -11]	2,685,651	0.004	0.090	-0.046	-0.003	0.043

Panel B. Fund-Level Summary Statistics

	Obs.	Mean	St. Dev.	Q1	Median	Q3
For daily flow-performance regression						
Daily fund flow (%)	1,974,170	0.025	0.962	-0.013	0.000	0.040
Daily return (net of fees, %)	1,974,170	0.002	0.824	-0.425	0.036	0.488
Fund characteristics						
Three-factor MKT	1,974,170	0.979	0.121	0.902	0.999	1.065
Three-factor SMB	1,974,170	0.174	0.213	0.020	0.119	0.277
Three-factor HML	1,974,170	-0.089	0.221	-0.192	-0.060	0.056
Fund TNA (KRW billions)	1,974,170	1.980	6.930	0.026	0.157	0.861
Management firm TNA (KRW billions)	1,974,170	153.0	155.0	31.40	96.40	237.0
Fund age (years)	1,974,170	6.197	3.942	2.778	6.016	9.225
Rear load ratio	1,974,170	0.044	0.206	0.000	0.000	0.000
Front load ratio	1,974,170	0.245	0.430	0.000	0.000	0.000
Top 10 holding team loss	1,974,170	0.404	0.491	0.000	0.000	1.000
Top 10 holding team win	1,974,170	0.395	0.489	0.000	0.000	1.000
Top 10 holding's 5-day number of losses	1,972,001	2.022	2.146	0.000	1.000	4.000
Top 10 holding's 5-day number of wins	1,972,001	1.980	2.109	0.000	1.000	4.000

Table 3. Do Baseball Game Results Affect Stock Returns?

This table presents OLS regression results of open-to-close daily stock return on the previous 5-day number of baseball game wins and losses as well as other controls. We do not include industry fixed effect in column (1), but with broadly-defined industry fixed effect in column (2), and narrowly-defined industry fixed effect in column (3). All specifications include day fixed effect. *t*-statistics computed from standard errors that are two-way clustered by stock and day are reported in parentheses. * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level, respectively.

	Excess Return (open-to-close) (%)		
	(1)	(2)	(3)
Previous 5-day number of losses	**-0.016****	**-0.016****	**-0.017*****
	(-2.37)	**(-2.45)**	**(-2.58)**
Previous 5-day number of wins	0.007	0.007	0.005
	(0.91)	(0.93)	(0.58)
Price	-0.005	-0.006	0.002
	(-1.24)	(-1.27)	(0.39)
Book-to-market	-0.030***	-0.031***	-0.048***
	(-5.31)	(-5.40)	(-8.53)
Log dollar volume	0.045***	0.045***	0.044***
	(9.77)	(9.87)	(9.98)
Log size	-0.055***	-0.054***	-0.054***
	(-8.84)	(-8.95)	(-9.09)
Log dividend yield	-0.080***	-0.079***	-0.084***
	(-11.59)	(-11.47)	(-12.29)
RET [-1]	3.276***	3.279***	3.292***
	(13.68)	(13.69)	(13.74)
RET [-5:-2]	1.770***	1.771***	1.789***
	(14.30)	(14.30)	(14.46)
RET [-10:-6]	0.190**	0.190**	0.206**
	(2.17)	(2.17)	(2.36)
RET [-20:-11]	0.358***	0.358***	0.368***
	(6.18)	(6.18)	(6.37)
Day Fixed Effect	YES	YES	YES
Industry Fixed Effect (Broad)	NO	YES	NO
Industry Fixed Effect (Narrow)	NO	NO	YES
No. of Obs.	2,685,651	2,683,321	2,685,651
Adjusted R-squared	0.207	0.207	0.208

Table 4. Who Drives the Sentiment Effect? Order Imbalance in Stock Market

This table presents OLS regression results of normalized order imbalance on previous 5-day baseball game wins and losses and lagged order imbalance terms up to five lags. Normalized order imbalance is calculated separately for individuals, foreigners, and institutions for each stock-day pair. *t*-statistics computed from standard errors that are two-way clustered by fund and day-time are reported in parentheses. * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level, respectively.

	Individuals (1)	Foreigners (2)	Institutions (3)
Previous 5-day number of losses	**-0.001***** **(-3.75)**	**0.002*** **(1.76)**	**-0.001** **(-0.56)**
Previous 5-day number of wins	**-0.000** **(-0.17)**	**0.002** **(0.86)**	**-0.001** **(-0.75)**
Order imbalance [t-1]	0.205*** (75.99)	0.187*** (40.71)	0.275*** (126.78)
Order imbalance [t-2]	0.126*** (102.93)	0.115*** (51.70)	0.137*** (62.42)
Order imbalance [t-3]	0.087*** (52.31)	0.073*** (49.60)	0.090*** (42.43)
Order imbalance [t-4]	0.068*** (55.26)	0.058*** (40.43)	0.071*** (32.88)
Order imbalance [t-5]	0.064*** (40.92)	0.049*** (34.79)	0.062*** (38.07)
Industry FE (broad)	Yes	Yes	Yes
Day FE	Yes	Yes	Yes
No. of Obs.	2,282,765	2,107,946	1,078,953
Adj. R-squared	0.150	0.147	0.238

Table 5. Baseball Sentiment and Fund Flow

This table presents OLS regression result of daily fund net flow on a fund's latest top 10 holdings' 5-day number of baseball game wins and losses as well as other controls. In addition to the controls, we include fund-type-by-day fixed effect. *t*-statistics computed from standard errors that are two-way clustered by fund and day are reported in parentheses. * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level, respectively

	Dependent Variable: Fund flow [0]
Top 10 holding's 5-day number of losses	**-0.003** **(-2.09)**
Top 10 holding's 5-day number of wins	**-0.001** **(-0.40)**
Daily net flow [-1]	0.170*** (46.08)
Daily net flow [-2]	0.131*** (38.67)
Dail net flow [-5: -3]	0.012*** (43.87)
Daily net flow [-10: -6]	0.000*** (16.46)
Daily return [-1]	0.309 (1.18)
Daily return [-2]	0.793*** (2.88)
Daily return [-5: -3]	1.263*** (7.03)
Daily return [-10: -6]	1.393*** (10.32)
Holding-level MKT [-1]	-0.053*** (-2.72)
Holding-level SMB [-1]	0.096*** (6.54)
Holding-level HML [-1]	0.008 (0.68)
Fund age [-1]	-0.008*** (-9.73)
Log management firm TNA [-1]	0.008*** (5.50)
Log fund share class TNA [-1]	-0.019*** (-19.28)

Rear load [-1]	-0.014* (-1.73)
Front load [-1]	-0.027*** (-5.87)
Expense ratio [-1]	-0.061*** (-11.63)
Fund type × day F.E.	Yes
No. of Obs. Adjusted R-squared	1,972,001 0.146

Table 6. Baseball Sentiment and Fund Flow: By Share Class Type

This table re-estimate OLS regression analysis in Table 5, albeit separately for (i) online-offline hybrid retail, (ii) online-only retail, (iii) all retail classes, and (iv) institutional classes. All controls and fixed effects are identical to Table 5. *t*-statistics computed from standard errors that are two-way clustered by fund and day are reported in parentheses. * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Panel A. Top 10 holding's during the previous 5-day

	Dependent variable: fund flow [0]			
	Hybrid Retail (1)	**Online Retail** **(2)**	Retail (3)	Institution (4)
Top 10 holding's 5-day number of losses	-0.002 (-1.04)	**-0.006**** **(-2.40)**	-0.003* (-1.91)	-0.000 (-0.02)
Top 10 holding's 5-day number of wins	-0.002 (-1.18)	**0.004** **(1.38)**	-0.001 (-0.42)	0.007 (0.93)
Controls	Yes	**Yes**	Yes	Yes
Fund type × day FE	Yes	**Yes**	Yes	Yes
No. of Obs.	1,346,641	**443,703**	1,791,329	25,505
Adjusted R-squared	0.142	**0.165**	0.150	0.062

Table 7. Calendar-Time Portfolio Analysis

This table presents calendar-time portfolio analysis. After every baseball game win or loss, we identify all funds that hold the conglomerate's members in their top 10 holdings then include these funds in the portfolios for a period of either 20 (Panel A) or 5 (Panel B) days. We then construct a win minus loss portfolio, purchasing all funds with winners in the top 10 holding and shorting all funds with losers in the top 10 holding. We do so both for the full sample as well as for each of the quintiles based on the previous one-year return. Calendar-time alphas are constructed using Carhart (1997) four-factor model. *t*-statistics computed from standard errors that are Newey-West corrected up to five lags are reported in parentheses. * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level, respectively.

Panel A. 20-day calendar-time portfolios

	Dependent Variable: loss weighted portfolio daily return – win weighted portfolio daily return					
	(1) Lowest return Quintile	(2) 2nd Quintile	(3) 3rd Quintile	(4) 4th Quintile	(5) Highest return Quintile	(6) All
Alpha[t]	**0.000**	**-0.001**	**0.000**	**-0.001**	**-0.001**	**0.001**
	(0.18)	**(-0.73)**	**(0.29)**	**(-0.84)**	**(-0.84)**	**(0.57)**
MKT[t]	0.000	0.001	0.001	0.002	0.000	0.002
	(0.25)	(0.75)	(1.10)	(0.97)	(0.04)	(1.40)
SMB[t]	-0.001	-0.003	-0.001	-0.002*	0.000	-0.002
	(-0.52)	(-1.59)	(-1.32)	(-1.72)	(0.27)	(-1.36)
HML[t]	0.000	0.005	0.001	0.002*	0.000	0.003
	(0.01)	(1.39)	(0.78)	(1.66)	(0.11)	(1.36)
UMD[t]	0.001	0.005*	0.002	0.002	-0.002	0.003
	(0.68)	(1.92)	(1.42)	(1.39)	(-1.37)	(1.30)
No. Obs.	959	959	960	958	958	964

Panel B. 5-day calendar-time portfolios

	Dependent Variable: loss weighted portfolio daily return – win weighted portfolio daily return					
	(1) Lowest return Quintile	(2) 2nd Quintile	(3) 3rd Quintile	(4) 4th Quintile	(5) Highest return Quintile	(6) All
Alpha[t]	**-0.001**	**-0.001**	**-0.001**	**0.003**	**0.004**	**0.001**
	(-0.23)	**(-0.53)**	**(-0.86)**	**(1.29)**	**(1.34)**	**(0.73)**
MKT[t]	-0.002	0.002	-0.000	-0.003	0.001	0.003
	(-0.71)	(0.54)	(-0.12)	(-1.51)	(0.20)	(1.00)
SMB[t]	-0.003	0.004	-0.002	-0.001	-0.002	0.003
	(-0.81)	(0.89)	(-1.64)	(-0.58)	(-0.43)	(0.87)
HML[t]	-0.002	-0.002	-0.002	-0.004	-0.002	-0.004
	(-0.76)	(-0.68)	(-0.91)	(-0.80)	(-0.44)	(-1.02)
UMD[t]	0.001	0.001	0.004	0.001	0.008*	0.003*
	(0.44)	(0.63)	(1.60)	(0.15)	(1.84)	(1.89)
No. Obs.	830	830	831	832	833	844

Table 8. Baseball Sentiment and Fund Flow: Business- vs. Consumer-Oriented Firms

This table presents re-estimates Table 5, albeit with the top 10 holding's previous-day wins and losses interacted with a business-oriented firm dummy. Business-oriented firms are manually identified using the segment-level sales data. *t*-statistics computed from standard errors that are two-way clustered by fund and day are reported in parentheses. * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level.

	Dependent Variable: Daily Fund Flow
	(1)
Top 10 holding's previous-day loss	-0.010**
	(-2.23)
Business-oriented firm dummy	-0.019**
	(-2.46)
Top 10 holding's previous-day loss × Business-oriented firm dummy	0.011
	(1.55)
Top 10 holding's previous-day win	-0.002
	(-0.39)
Top 10 holding's previous-day win × Business-oriented firm dummy	0.001
	(0.17)
Fund type × day FE	Yes
Controls	Yes
No. of Obs.	1,974,170
Adjusted R-squared	0.146

Table 9. Baseball Sentiment and Fund Flow: Changes in League Rankings

This table re-estimates Table 5, albeit with two additional indicator variables that identify losses and wins that result in the baseball team's loss or gain of the league table ranking. Any fund that holds such a team's constituent member in its top 10 holding on the day is assigned a value of one in the indicator variable. Controls and fixed effects are identical to Table 5. *t*-statistics computed from standard errors that are two-way clustered by fund and day-time are reported in parentheses. * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level, respectively.

	Dependent Variable: Daily Fund Flow
Rank Down After loss	**-0.009*** **(-1.67)**
Rank Up After win	**-0.004** **(-0.57)**
Top 10 holding's 5-day number of losses	-0.001 (-0.74)
Top 10 holding's 5-day number of wins	0.001 (0.94)
Controls	Yes
Fund type × day FE	Yes
No. of Obs. Adjusted R-squared	891,430 0.160

Table 10. Baseball Sentiment and Fund Flow: Post-Season Games

This table re-estimates Table 5, albeit with two indicator variables separating top 10 holdings' 5-day number of losses and wins during the post-season from the other regular season games. Controls and fixed effects are identical to Table 5. *t*-statistics computed from standard errors that are two-way clustered by fund and day-time are reported in parentheses. * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level, respectively.

	Dependent Variable: Daily Fund Flow
Top 10 holding's 5-day number of losses in post-season	**-0.034** (-2.02)**
Top 10 holding's 5-day number of wins in post-season	**0.027 (1.36)**
Top 10 holding's 5-day number of losses	-0.003** (-2.06)
Top 10 holding's 5-day number of wins	-0.001 (-0.42)
Controls	Yes
Fund type × Time FE	Yes
No. of Obs. Adjusted R-squared	1,972,001 0.146

Table 11. Baseball Sentiment and Fund Flow: Game Margin

This table re-estimates Table 5, but with two additional sets of variables indicating narrow games (with the margin of final score of one) and wide margin games (with the margin of final score of five or greater). Controls and fixed effects are identical to Table 5. *t*-statistics computed from standard errors that are two-way clustered by fund and day-time are reported in parentheses. * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level, respectively.

	Dependent Variable: Daily Fund Flow
Top 10 holding's 5-day number of losses	-0.007 (-1.42)
Top 10 holding's 5-day number of wins	-0.007 (-1.18)
Narrow margin loss	**-0.007*** **(-1.71)**
Narrow margin win	-0.002 (-0.42)
Wide margin loss	-0.001 (-0.20)
Wide margin win	0.006 (1.10)
Controls	Yes
Zero-in Fund Type F.E. Time F.E.	Yes
N adj. R-sq	1,974,170 0.146

Figure 1. Number of Spectators Per Game Among Major Korean Professional Sports

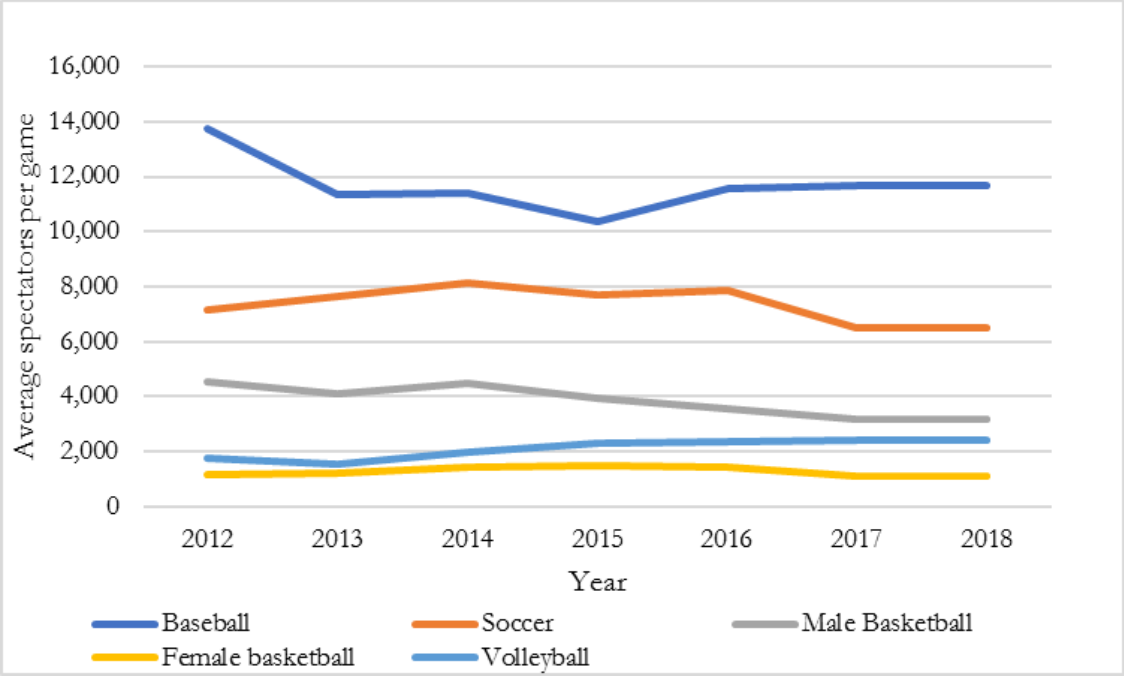
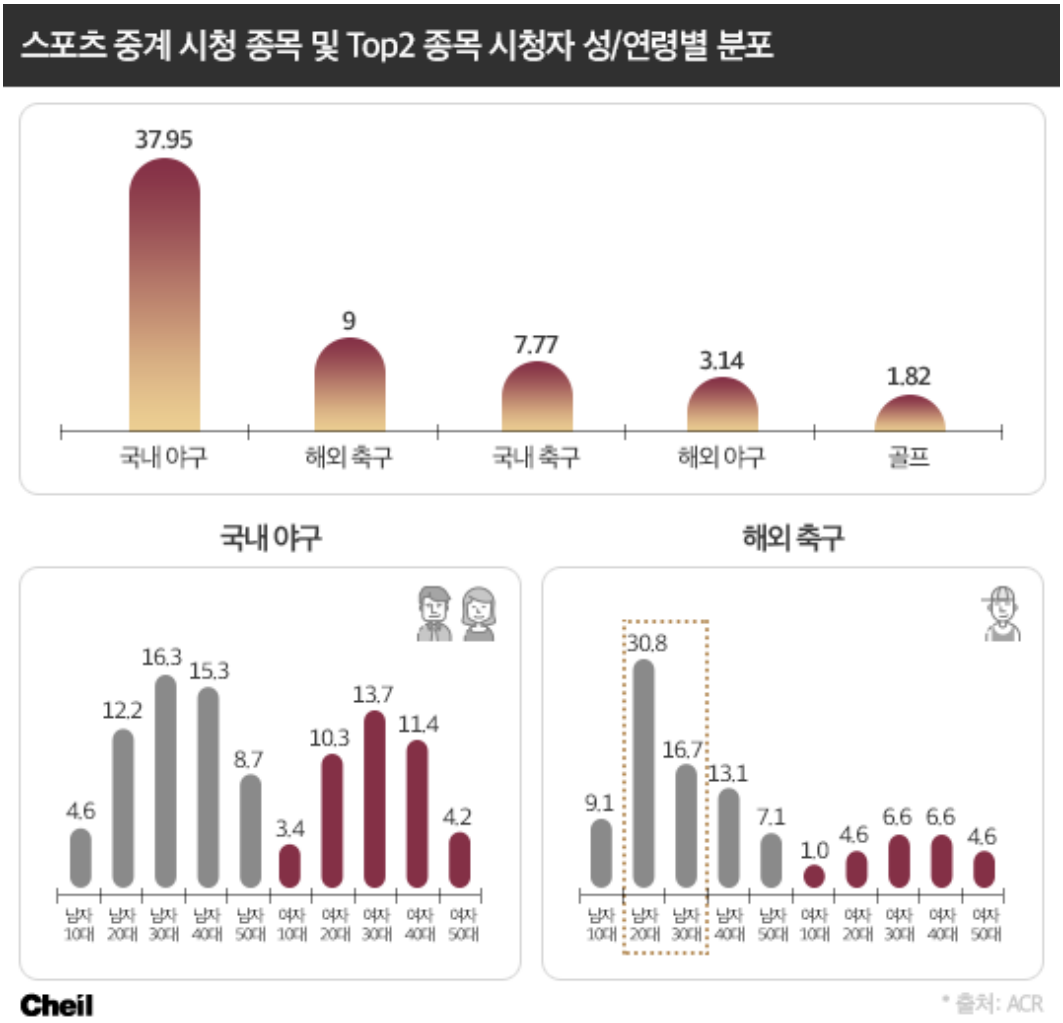


Figure 2. Age and Gender Demographics of Sports Fan Base

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