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Sports Sentiment and Stock Returns

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ABSTRACT

This paper investigates the stock market reaction to sudden changes in investor mood. Motivated by psychological evidence of a strong link between soccer outcomes and mood, we use international soccer results as our primary mood variable. We find a significant market decline after soccer losses. For example, a loss in the World Cup elimination stage leads to a next-day abnormal stock return of −49 basis points. This loss effect is stronger in small stocks and in more important games, and is robust to methodological changes. We also document a loss effect after international cricket, rugby, and basketball games.

THIS PAPER EMPLOYS A NOVEL MOOD VARIABLE, international soccer results, to investigate the effect of investor sentiment on asset prices. Using a cross-section of 39 countries, we find that losses in soccer matches have an economically and statistically significant negative effect on the losing country's stock market. For example, elimination from a major international soccer tournament is associated with a next-day return on the national stock market index that is 38 basis points lower than average. We also document a loss effect after international cricket, rugby, and basketball games. On average, the effect is smaller in magnitude for these other sports than for soccer, but is still economically and statistically significant. We find no evidence of a corresponding effect after wins for any of the sports that we study. Controlling for the pre-game expected outcome, we are able to reject the hypothesis that the loss effect after soccer games is driven by economic factors such as reduced productivity or lost revenues. We

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also document that the effect is stronger in small stocks, which other studies find are disproportionately held by local investors and more strongly affected by sentiment. Overall, our interpretation of the evidence is that the loss effect is caused by a change in investor mood.

Our study is part of a recent literature that investigates the asset pricing impact of behavioral biases documented in psychology research. This literature, which has expanded significantly over the last decade, is comprehensively reviewed by Hirshleifer (2001) and Shiller (2000). The strand of the literature closest to this paper investigates the effect of investor mood on asset prices. The two principal approaches in this work link returns either to a single event or to a continuous variable that impacts mood. Examples of the event study approach are Kamstra, Kramer, and Levi (2000), who investigate the impact of disruption to sleep patterns caused by changes to and from daylight saving, and Frieder and Subrahmanyam (2004), who study nonsecular holidays. With respect to the continuous variable literature, Saunders (1993) and Hirshleifer and Shumway (2003) study the impact of sunshine, Cao and Wei (2005) examine temperature, Kamstra, Kramer, and Levi (2003) analyze daylight, and Yuan, Zheng, and Zhu (2006) explore lunar cycles. The main advantage of the event approach compared to the use of a continuous variable is that the former clearly identifies a sudden change in the mood of investors, which gives a large signal-to-noise ratio in returns. The main disadvantage of the event approach is that the number of observed signals tends to be low, which reduces statistical power.

Our main contribution is to study a variable, international soccer results, that has particularly attractive properties as a measure of mood. While extensive psychological evidence, which we review below, shows that sports in general have a significant effect on mood, TV viewing figures, media coverage, and merchandise sales suggest that soccer in particular is of "national interest" in many of the countries we study.[1] It is hard to imagine other regular events that produce such substantial and correlated mood swings in a large proportion of a country's population. These characteristics provide strong a priori motivation for using game outcomes to capture mood changes among investors. This is a key strength of our study, since such a measure of mood changes mitigates concerns about data mining.

The large loss effect that we report reinforces the findings Kamstra et al. (2000), who document a stock market effect of similar magnitude in response to the daylight saving clock change. While Pinegar (2002) argues that the "daylight saving anomaly" is sensitive to outliers, our effect remains economically and statistically significant even after removing outliers in the data and applying a number of robustness checks. Another contribution of this paper is that we are able to go a long way toward addressing the main disadvantage of the

[1] Several countries even require the public broadcaster to show national soccer games live and cable channels are not permitted to bid for the rights to the games. In countries such as Italy, Spain, Greece, and Portugal, the best-selling newspapers are dedicated exclusively to sports, particularly soccer.

event approach. Our sample of soccer matches exceeds 1,100 observations, and exhibits significant cross-sectional variation across nations. In addition, we study more than 1,500 cricket, rugby, ice hockey, and basketball games.[2] The full sample of 2,600 independent observations compares favorably to existing mood-event studies.

The rest of the paper is organized as follows. Section I explains the a priori motivations for investigating the link between sports and stock returns. In Section II we describe the data, and in particular the competitions that are the subject of our study. Section III documents an economically and statistically significant loss effect. Section IV distinguishes between behavioral and economic explanations for this effect. Section V summarizes our findings and concludes.

I. Motivation

A number of recent papers document a link between mood and stock returns. Concerns that such results are the product of data mining call for investigating a new mood variable, or testing an existing mood variable on an independent sample to confirm results of previous studies. For example, Hirshleifer and Shumway (2003) confirm and extend the sunlight effect first documented by Saunders (1993). Since the null hypothesis is that markets are efficient, such investigations should include a clear unidirectional alternative hypothesis, limiting the possibility of a rejection of the null in any direction. For example, Frieder and Subrahmanyam (2004) find abnormally positive returns around Yom Kippur and St. Patrick's Day and negative returns around Rosh Hashanah, without specifying a priori why positive returns should arise with certain religious holidays and negative returns with others.

With the above in mind, we argue that a mood variable must satisfy three key characteristics to rationalize studying its link with stock returns. First, the given variable must drive mood in a substantial and unambiguous way, so that its effect is powerful enough to show up in asset prices. Second, the variable must impact the mood of a large proportion of the population, so that it is likely to affect enough investors. Third, the effect must be correlated across the majority of individuals within a country.

We believe that international soccer results satisfy these three criteria. An abundance of psychological evidence shows that sports results in general have a significant effect on mood. For example, Wann et al. (1994) document that fans often experience a strong positive reaction when their team performs well and a corresponding negative reaction when the team performs poorly. More importantly, such reactions extend to increased or decreased self-esteem and

[2] Ashton, Gerrard, and Hudson (2003) and Boyle and Walter (2002) study the stock market effect of soccer in England and rugby in New Zealand, respectively. Ashton, Gerrard, and Hudson (2003) argue that the effect of wins and losses is symmetric. Boyle and Walter (2002) conclude, with similar point estimates to those in this paper, that there is no evidence in favor of any effect of rugby on New Zealand's stock market. Both conclusions stand in sharp contrast to our large-sample evidence.

to positive or negative feelings about life in general. Hirt et al. (1992) find that Indiana University college students estimate their own performance to be significantly better after watching a win by their college basketball team than after watching a loss. Schwarz et al. (1987) document that the outcome of two games played by Germany in the 1982 World Cup significantly changed subjects' assessments of their own well-being and their views on national issues. A related study by Schweitzer et al. (1992) shows that assessments of both the probability of a 1990 war in Iraq and its potential casualties were significantly lower among students rooting for the winning team of a televised American football game than among fans of the losing team. Changes in mood also affect economic behavior. Arkes, Herren, and Isen (1988) find that sales of Ohio State lottery tickets increase in the days after a victory by the Ohio State University football team. Given the evidence that sports results affect subjects' optimism or pessimism about not just their own abilities, but life in general, we hypothesize that they impact investors' views on future stock prices.[3]

Note that as a testament to the fundamental importance of sports, the effects of sports results extend far beyond simple mood changes. For instance, in many cases sport results have such a strong effect that they adversely affect health. Carroll et al. (2002) show that admissions for heart attacks increased 25% during the 3-day period starting June 30, 1998, the day England lost to Argentina in a World Cup penalty shoot-out.[4] Further, White (1989) documents that elimination from the U.S. National Football League playoffs leads to a significant increase in homicides in the relevant cities following the games, and Wann et al. (2001) list several cases of riots after disappointing sports results, citing a multitude of other papers on the same issue. Trovato (1998) also finds that suicides among Canadians rise significantly if the Montreal Canadians are eliminated early from the Stanley Cup playoffs.

While a large body of the literature shows that sporting events in general impact human behavior, a significant amount of evidence suggests that soccer in particular is an important part of many people's lives. For example, the cumulative number of television viewers that followed the 2002 World Cup in Korea/Japan exceeded 25 billion, the final between Brazil and Germany was viewed by more than 1 billion, and on average more than 20 (10) million viewers from Italy (Spain and England) watch their national team in the final stages of the World Cup or European Championship[5] Moreover, national soccer results influence the mood of an entire country in a similar way, whereas other popular sports, such as American football and baseball, are predominantly contested on

[3] For other related studies see Sloan (1979), Wann and Branscombe (1995), Platow et al. (1999), and Bizman and Yinon (2002).

[4] See Berthier and Boulay (2003) and Chi and Kloner (2003) for more recent studies with similar conclusions.

[5] These figures are substantially greater than those for other sports. We obtained TV viewership data for England using news searches in factiva.com and google.com (extensive viewing figures are unavailable for other countries). These viewership figures show that all the top 30 sport events in England in 2000 were associated with soccer, with the exception of the Grand National (horse racing).

a club rather than country level. The "home bias" documented by French and Poterba (1991) means that the individuals affected are also likely to be the marginal investors in the domestic stock market.[6] Thus, international soccer matches are among the very few events that take place at regular intervals and that are perceived as important by a large fraction of the population in a broad range of countries, and as such are interesting to study. Accordingly, soccer serves as our primary sport for analysis.

To increase our sample size, we also investigate the impact of cricket, rugby, ice hockey, and basketball results. These sports also involve regular international competition and are important in a number of countries. However, we expect any results to be strongest in relation to soccer, given it is the number one sport in most of the countries we study, often by a substantial margin.

The psychology literature documents a significant difference in the behavior of fans following wins and losses. Specifically, while an increase in heart attacks, crimes, and suicides is shown to accompany sporting losses, there is no evidence of improvements in mood of a similar magnitude after wins. This asymmetry suggests that we should observe a greater effect after soccer losses than after soccer wins.[7] A similar prediction follows from the prospect theory of Kahneman and Tversky (1979). At the heart of prospect theory is its reliance on gains and losses as carriers of utility, rather than wealth levels. That is, the reference point against which gains and losses are measured becomes an important determinant of utility. The natural reference point in our setting is that of supporters' pre-game expectations of how their team will perform. A number of studies show that fans are subject to an "allegiance bias," whereby individuals who are psychologically invested in a desired outcome generate biased predictions (see Markman and Hirt (2002), Wann et al. (2001)). Thus, if the reference point of soccer fans is that their team will win, we may find a greater stock price reaction after losses than after wins. A third reason to expect an asymmetric reaction to wins and losses, specific to elimination games, results from the inherent asymmetry of the competition format. While a win merely advances a country to the next stage, a loss immediately removes the country from the competition.

II. The Data

We collect international soccer results from January 1973 through December 2004 from the website www.rdasilva.demon.co.uk. The data include games from the World Cup and the main continental cups (European Championship, Copa America, and Asian Cup).

[6] French and Poterba (1991) find that the domestic ownership shares of the world's five largest stock markets lie between 79% and 96%. This is confirmed by a multitude of further studies, summarized by Karolyi and Stulz (2003).

[7] The psychology literature also hints at the possibility of win effects being larger than loss effects. According to behavioral patterns known as "basking in reflected glory" (BIRGing) and "cutting off reflected failure" (CORFing), fans cut their association with losing teams and increase their association with winning teams. See, for example, the discussion in Hirt et al. (1992).

International soccer competitions have used slightly different formats throughout the last 30 years. With respect to the World Cup, as of 2004, national teams from different geographic regions play against each other to qualify for the Cup. We refer to games at this stage as "qualifying games." Based on performance in the qualifying rounds, 32 teams are selected as competitors for the World Cup. The teams are divided into groups of four. We refer to games in this stage as "group games." Teams in each group play against each other with the top two advancing to the "elimination stage." In this stage, which starts with 16 teams, no ties are allowed. Thus, at each of the following stages, half of the remaining teams are eliminated. The team that survives all elimination matches wins the World Cup. The European Championship, Copa America, and Asian Cup follow a similar format to determine the winner.

The international soccer sample comprises matches played by 39 different countries (see the Appendix for country selection and Table AI for details). We classify a total of 1,162 soccer matches, 638 wins and 524 losses, as relevant "mood events." This set of mood events includes all elimination and group games in the World Cup and the continental cups, that is, 756 games, plus another 406 relevant qualifying games. Owing to the large disparity in skill across participating countries in a typical qualifying group, a national team will usually play only four to six matches that will be critical for its qualification and that in turn will have a significant mood impact.[8] To select games that have a reasonable chance of being important, we use closeness in the ability of the two opponents as a proxy for importance, where ability is measured using Elo ratings (www.eloratings.net).[9] A qualifying game is defined as close if the Elo rating of the two opponents is within 125 points (after adding 100 points to the team with the home advantage) or if the game is played as part of the knockout stage between the qualifying rounds and the group stage. As of October 31, 2005, the difference in Elo ratings between the top-ranked country (Brazil) and the 10th country (Portugal) is 122 points.

We collect the data on cricket, rugby, ice hockey, and basketball from various web sources. The cricket matches come from One Day Internationals played over the period 1975 to 2004; the rugby matches from the Six Nations (England, France, Ireland, Italy, Scotland, and Wales), Tri Nations (Australia, New Zealand, and South Africa), and World Cup competitions between 1973 and 2004; the ice hockey matches from the World Championships (1998 to 2004), Olympics (1980 to 2002), and World Cup/Canada Cup (1996 and 2004); and the basketball matches from the Olympics (1992 to 2004) and World Championships (1994 to 2002). The Appendix describes data sources and the details of the sample selection for all sports. The sample of cricket, rugby, ice hockey, and basketball matches contains 905 wins and 645 losses for 24 countries. This

[8] Strong soccer nations such as England, Italy, and Spain may play in the same groups as substantially weaker nations such as Malta, San Marino, and Luxembourg. Games against weak opposition are less likely to generate any interest, and are therefore less interesting as mood events.

[9] Elo ratings, developed by Arpad Elo, are best known as the rating system used in chess to rank players. These ratings have started to become popular for paired comparisons in other sports.

gives on average 388 games for each of these four sports. However, about 45% of the other-sport sample consists of rugby games, due to both longer time series of stock returns for rugby nations and the greater regularity of rugby games.

The market indices used in this study are from Datastream. We compute returns using a total return index (assuming that dividends are reinvested). If the total return index is not available, we use a price index instead. Index returns are measured in the local currency since the biases we have in mind are associated with domestic investors, for which local returns are the relevant benchmark. The Appendix reports the details on the indices used in this study.

III. Results

To measure the effect of international sports results on stock prices, we use the return on a broad stock market index on the first trading day following the game. Although for some weekday games the market is open while the match is being played, we choose to use the first trading day after the match for all games to ensure that we have the return for a full day when the game outcome is known. If anything, this potential asynchrony attenuates our results since part of the reaction may have been incorporated in prices before our measurement day.

A. Descriptive Statistics

Table I provides information about the number of games included in the sample for each sport, as well as mean daily log stock market returns on days following game days and non-game days. For the sample of soccer countries in Panel A, 181,796 trading days are not associated with a soccer match. The average return and standard deviation for these days are 5.8 and 144.9 basis points, respectively. The average return on days after an international soccer win is positive (5.0 basis points), but negative and significantly lower on days following a loss (−18.4 basis points). The standard deviation of returns is slightly higher after game days than for other days, but the difference is only minor. Looking across the different cups and stages in the competition, it is apparent that the loss effect is most pronounced for World Cup games and elimination games in general. A similar win-loss pattern shows up in the returns after other sports results in Panel B of Table I. For the 645 loss days, the average return is −15.3 basis points. The loss effect seems to be more pronounced for cricket and basketball, with the cricket point estimates consistent with the sport's importance in South Asia. The average return on the 903 win days is −4.0 basis points, with positive point estimates only for the ice hockey and basketball subsamples.

In Panels A and B, we have a total of 10 independent subsamples of games. It is reasonable to assume that the stock returns associated with a game will be independent across these groups. In Panel A, the difference between average returns after win days and loss days is always positive, with a maximum of over 50 basis points for World Cup elimination games. In Panel B the differences are

Table I

Number of Wins and Losses in International Team Sport Matches and Percent Mean Daily Return on the First Trading Day after Matches

The table reports the number of wins and losses in international soccer, cricket, rugby, ice hockey, and basketball matches. The soccer matches are played over the period 1973 to 2004 in the World Cup, European Championship, Copa America, Asian Cup, World Cup qualifying stages, and European Championship qualifying stages. The cricket matches are One Day Internationals played over the period 1975 to 2004. The rugby matches are Six Nations, Tri Nations, and World Cup matches between 1973 and 2004. The ice hockey matches are the World Championships (1998 to 2004), Olympics (1980 to 2002), and World Cup/Canada Cup (1996 and 2004) competitions. The basketball matches are the Olympics (1992 to 2004) and World Championships (1994 to 2002) tournaments. The mean returns reported in the table are computed from the log daily return on national stock market indices (from Datastream) on the first trading day after wins and losses. The Appendix details the country selection for each sport. Elimination matches are matches in which the loser is eliminated from further play in the tournament. Group games are played during the championship and qualify teams for the elimination stage. Close qualifying games are played to qualify for the championship by two teams with a difference in Elo rating below 125 points, after adding 100 points to the team with home advantage.

	No Games			Wins			Losses		
	N	Mean	*SD*	*N*	Mean	*SD*	*N*	Mean	*SD*
Panel A: International Soccer (39 Countries)									
No games	181,796	0.058	1.449						
All games				638	0.050	1.474	524	−0.184	1.547
World Cup elimination games				76	0.172	1.306	56	−0.359	1.901
World Cup group games				115	−0.067	1.535	81	−0.516	1.329
World Cup close qualifying games				137	−0.067	2.089	122	−0.074	1.304
Continental cups elimination games				101	−0.044	1.021	82	−0.330	1.544
Continental cups group games				128	0.164	1.186	117	0.035	1.838
European Champ. close qualifying games				81	0.239	1.121	66	−0.036	1.235
Panel B: Other International Team Sports (25 Countries)									
No games	120,416	0.054	1.438						
All games				903	−0.040	1.823	645	−0.153	1.838
Cricket				153	−0.071	2.908	88	−0.210	3.413
Rugby				403	−0.161	1.117	307	−0.152	1.091
Ice hockey				238	0.139	1.707	148	−0.018	1.305
Basketball				111	0.071	2.166	102	−0.302	2.315

positive with the exception of the rugby subsample, for which the difference is negative, but by less than one basis point. Therefore, in 9 of the 10 subgroups the point estimates show a positive difference between win and loss days. The probability that there are 9 or more successes out of 10 equally likely Bernoulli trials is 1%. Thus, the null hypothesis of a similar return after wins and losses

can be easily rejected at conventional levels of statistical significance. In sum, even ignoring the actual size of the differences, the evidence in Table I suggests that sports results are indeed correlated with stock returns.

An important property of the soccer events we study is that they are clustered around a few weeks, mostly in the months of June and July for the World Cup, European Championship, and Copa America. For example, even though we have 177 distinct elimination games with wins and 138 with losses, there are only 113 distinct days in our database for which at least one country won and only 96 days for which at least one country lost. To the extent there are common shocks to stock returns across different countries, return observations on event dates will not be independent. Moreover, for all the sports, because many matches are played between Friday afternoon and Sunday afternoon, we measure the daily return on Monday for all these games. This may introduce a spurious day-of-the-week relationship between soccer results and stock returns. The next section details the econometric approach we follow to deal with these and other issues that may influence our results.

B. Econometric Approach

Our null hypothesis is that stock markets are unaffected by the outcomes of soccer matches. This null hypothesis embeds the view that investors are rational, that markets are efficient, and that the economic benefits associated with winning an international soccer game are too small to influence the national stock market index. The alternative hypothesis is that wins lead to a positive stock market reaction and losses lead to a negative reaction. This is motivated by the findings from the psychology literature that suggest wins are associated with a good mood and losses with a bad mood.

Under the null hypothesis, soccer outcomes are uncorrelated with asset prices. This in turn implies that the effects of soccer should be consistently estimated with *any* model of stock returns—even one that is completely misspecified.[10] To estimate the impact of wins and losses on stock returns while controlling for the Monday effect and other confounding effects, we first estimate the following model for each country i:

$$R_{it} = \gamma_{0i} + \gamma_{1i} R_{it-1} + \gamma_{2i} R_{mt-1} + \gamma_{3i} R_{mt} + \gamma_{4i} R_{mt+1} + \gamma_{5i} D_t + \gamma_{6i} Q_t + \epsilon_{it}, \qquad (1)$$

where R_{it} is the continuously compounded daily local currency return on a broadly based stock market index for country i on day t, R_{mt} is the continuously compounded daily U.S. dollar return on Datastream's world market index on day t, $D_t = \{D_{1t}, D_{2t}, D_{3t}, D_{4t}\}$ are dummy variables for Monday through Thursday, and $Q_t = \{Q_{1t}, Q_{2t}, Q_{3t}, Q_{4t}, Q_{5t}\}$ are dummy variables for days for which the previous 1 through 5 days are non-weekend holidays.

The model specification in (1) is motivated by previous studies of the time-series variability of stock returns. The lagged index return, R_{it-1}, is included to

[10] This follows from the fact that omitted variables do not bias coefficient estimates in a regression when the omitted variable is independent of other regressors.

account for first-order serial correlation. To the extent that international stock markets are integrated, the return on local indices will be correlated across countries. The contemporaneous return on the world market portfolio, R_{mt}, is included to control for this correlation. Since some local markets may be lagging the world index while other may be leading the index, the model also includes R_{mt-1} and R_{mt+1}. We estimate the model simultaneously for all countries by interacting each independent variable with a set of country dummies. For the sample of 39 soccer nations, the adjusted R^2 for this regression is 15%.

Let $\hat{\epsilon}_{it}$ denote the residuals from regression (1). We estimate the effect of the outcome of international soccer matches using the regression model

$$\hat{\epsilon}_{it} = \beta_0 + \beta_W W_{it} + \beta_L L_{it} + u_{it}, \tag{2}$$

where $W_{it} = \{W_{1it}, W_{2it}, \ldots, \}$ are dummy variables for wins in different game subgroups and $L_{it} = \{L_{1it}, L_{2it}, \ldots, \}$ are loss dummies for the same set of game subgroups. The number of game subgroups will vary depending on the setting. More specifically, W_{git} is a dummy variable that equals one if country i wins a soccer match in game subgroup g (e.g., a World Cup elimination game) on a day that makes t the first trading day after the match and zero otherwise; L_{git}, a dummy variable for losses, is defined analogously to the win dummy. As in Hirshleifer and Shumway (2003), we estimate the above model using panel-corrected standard errors (PCSE), which assumes that the error terms u_{it} are mean zero and uncorrelated over time, but allows for heteroskedasticity and contemporaneous correlation across countries.

One possible concern regarding the above statistical specification is its constant-volatility assumption. French, Schwert, and Stambaugh (1987) and Bollerslev, Engle, and Nelson (1994), among others, show that stock index returns have time-varying volatility. Thus, if any of our international competitions occurred during periods of high volatility, the magnitude of our standard errors would be biased downward. To address this issue we model stock return volatility using a GARCH model as developed by Engle (1982) and generalized by Bollerslev (1986). Specifically, after modeling stock returns using equation (1), we model the volatility of the error term from this regression as the GARCH(1,1) process $\sigma_{it}^2 = \lambda_{0i} + \lambda_{1i}\epsilon_{it-1}^2 + \lambda_{2i}\sigma_{it-1}^2$, where σ_{it}^2 is the index return volatility for country i on day t. We then use the time series $\hat{\sigma}_{it}^2$ to form the new time series of normalized stock index returns $R_{it}^0 = a_i + b_i(1/\hat{\sigma}_{it})R_{it}$, where a_i and b_i are chosen so that the mean of R_{it}^0 is equal to zero and the standard deviation is equal to one. By normalizing all index returns we eliminate the heterogeneity in volatility across countries in addition to the time-series variation adjustment of the GARCH model. The normalized returns, R_{it}^0, are then used in the model specification (1), from which we obtain a second set of normalized residuals, which we denote by $\tilde{\epsilon}_{it}$. For the most part, we conduct our analysis on the normalized residuals $\tilde{\epsilon}_{it}$. To distinguish these residuals from the residuals $\hat{\epsilon}_{it}$, we refer to the latter as "abnormal raw returns" and the former as "abnormal normalized returns."

C. The Loss Effect

Table II reports the main findings of this paper. Panel A details results using abnormal raw returns for matches played in the eight World Cups and all continental cups between 1974 and 2004. Focusing first on the results for losses on the right-hand side of Panel A, the most striking finding is that national stock markets earn a statistically and economically significant negative return on the day after a loss by the national soccer team. The ordinary least squares (OLS) coefficient on the loss dummy is −38.4 basis points for the 138 elimination games, and a staggering −49.4 basis points for the 56 World Cup elimination games. The point estimates are consistently negative for all six subsets of games.

The point estimate for the loss effect is increasing in game importance. First, the World Cup games show a bigger loss effect than the continental cup games for all three game groups. Second, the loss effect for elimination games is larger than for group games, which in turn show a larger loss effect than close qualifying games. It seems natural to argue that elimination games in the final stages of a soccer competition should have the strongest mood effect, as such games receive the greatest media coverage and a loss in an elimination game immediately sends a national team home. Moreover, some losses in group or qualifying games may be irrelevant (because a team already qualified or no longer has a chance of qualification due to performance in earlier group games) or may not yield immediate elimination (since a team can recover by winning subsequent group games).

For the full sample of 524 soccer losses, the point estimate is −21.2 basis points, highly significant both in economic and statistical terms. We reject the null hypothesis of $\beta_L = 0$ at any conventional level using PCSE. The win coefficient is a positive 1.6 basis points for the overall sample and a positive 9.0 basis points for World Cup elimination games. However, these estimates are not statistically distinguishable from zero. The large negative effect for losses and smaller positive effect for wins is consistent with the inherent asymmetry between elimination wins and losses. While a loss leads to instant exit, a win merely advances the team to the next round. Thus, the attention of fans after a win may quickly turn to the next stage of matches. This may be exacerbated by an allegiance bias in fans' expectations regarding the game outcome. If fans overestimate the probability of a national team win, losses will have a particularly dramatic effect.

Panel B in Table II reports the results using the abnormal normalized returns described in Section III.B. Since the estimates on these normalized returns give less weight to observations in countries with volatile stock markets, game-day observations that come from extreme returns in highly volatile markets will have a smaller impact on the point estimate. The results on the right-hand side of Panel B confirm the findings from Panel A. The loss effect is unaffected by the GARCH(1,1) volatility adjustment; if anything, the GARCH adjustment and the normalization of returns increase the statistical power to reject the null hypothesis. In order to interpret the size of the coefficient estimates, and

Table II

Abnormal Daily Stock Market Performance after International Soccer Matches

The analysis is based on soccer wins and losses for 39 countries (see the Appendix). The average time series has 4,690 trading days, which gives a total of 182,919 daily return observations. The table reports the ordinary least squares (OLS) estimates of β_W and β_L from

$$\epsilon_{it} = \beta_0 + \beta_W W_{it} + \beta_L L_{it} + u_{it},$$

where u_{it} is an error term that is allowed to be heteroskedastic and contemporaneously correlated across countries, W_{it} is a dummy variable that takes the value one if country i wins a soccer match on a day that makes t the first trading day after the match and zero otherwise, and L_{it} is a dummy variable for losses defined analogously. If games are mutually exclusive (such as elimination games, group games, and qualifying matches), W_{it} and L_{it} are vectors, where each element corresponds to a game type. In Panel A the ϵ_{it}'s are the "raw residuals" $\hat{\epsilon}_{it}$ defined by the regression

$$R_{it} = \gamma_{0i} + \gamma_{1i} R_{it-1} + \gamma_{2i} R_{mt-1} + \gamma_{3i} R_{mt} + \gamma_{4i} R_{mt+1} + \gamma_{5i} D_t + \gamma_{6i} Q_t + \hat{\epsilon}_{it},$$

where R_{it} denotes the continuously compounded local return on date t in country i, R_{mt} is the continuously compounded daily U.S. dollar return on Datastream's world market index on day t, $D_t = \{D_{1t}, D_{2t}, D_{3t}, D_{4t}\}$ are dummy variables for Monday through Thursday, and $Q_t = \{Q_{1t}, Q_{2t}, Q_{3t}, Q_{4t}, Q_{5t}\}$ are dummy variables for days for which the previous 1 through 5 days are non-weekend holidays. Panel B reports the estimates for β_W and β_L when the "abnormal normalized returns" defined in Section III.B are used in the panel regression. These normalized residuals are the second-stage residuals of a panel regression such as the one for $\hat{\epsilon}_{it}$ after a GARCH correction and normalizing them to have unit variance. The reported t-statistic is computed by allowing the variance of u_{it} to be country specific (i.e., σ_i^2 is estimated for all countries) and by allowing for contemporaneous cross-country correlations (σ_{ij} is estimated for all pairs of countries). See the caption in Table I and the Appendix for sample details.

	Wins			Losses		
	Number of Games	β_W	t-Values	Number of Games	β_L	t-Values
Panel A: Abnormal Raw Returns						
All games	638	0.016	0.27	524	−0.212	−3.27
Elimination games	177	0.046	0.43	138	−0.384	−3.24
World Cup elimination games	76	0.090	0.53	56	−0.494	−2.71
Continental cups elimination games	101	0.013	0.09	82	−0.309	−1.99
Group games	243	0.052	0.53	198	−0.168	−1.47
World Cup group games	115	0.007	0.05	81	−0.380	−2.23
Continental cups group games	128	0.092	0.67	117	−0.022	−0.14
Close qualifying games	218	−0.049	−0.52	188	−0.131	−1.29
World Cup close qualifying games	137	−0.095	−0.78	122	−0.132	−1.05
European Championship close qualifying games	81	0.029	0.19	66	−0.130	−0.75
Panel B: Abnormal Normalized Returns						
All games	638	−0.019	−0.47	524	−0.157	−3.68
Elimination games	177	0.026	0.35	138	−0.182	−2.17
Group games	243	−0.034	−0.52	198	−0.179	−2.57
Close qualifying games	218	−0.038	−0.58	188	−0.116	−1.65

thereby measure economic significance, notice that $\beta_L = -0.157$ for all games implies an average return that is 0.157 standard deviations below its mean. For a stock market index with daily volatility of 1.449 basis points (see Panel A Table I), this translates into an abnormal raw return of $0.157 \times 1.449 = 0.23$, which is almost identical to the point estimate for raw abnormal returns from Panel A. Turning to the left-hand side of Panel B, the results from Panel A are again confirmed. There is no evidence of any abnormal stock market returns after wins. The win coefficients are virtually zero for all game subsets and are statistically indistinguishable from zero.[11]

When comparing across competitions and stages in Panel A of Table II, it appears that the loss effect is increasing in game importance. In Table III we explore this issue further by investigating whether the effect is stronger in countries in which soccer is of greatest importance. We split the sample into "Top Seven soccer nations" and "Other soccer nations." The Top Seven soccer nations are Argentina, Brazil, England, France, Germany, Italy, and Spain.[12] The remaining 32 countries are referred to as Other soccer nations. Panel A of Table III contains the results for the Top Seven countries while Panel B contains results for the Other countries. Comparing corresponding point estimates in the two panels, the point estimates for the Top Seven are larger in magnitude for all wins and all losses except for continental group games. However, an economically and statistically significant loss effect still exists for Other countries, so the effect documented in Table II is not driven purely by the Top Seven. The strength of the effect in Other countries, coupled with the high standard errors, prevents us from statistically rejecting the hypothesis that all point estimates in Panel A are equal to the corresponding point estimates in Panel B.[13]

D. Statistical Robustness Checks

This section investigates the robustness of the loss effect by controlling for the clustering of games on certain dates and by eliminating the effect of outliers in the data. For brevity we report results only on normalized returns—the results using raw returns are virtually identical.

A potentially important problem with our data is the time-clustering of observations. Although equation (1) controls for market movements, we may be

[11] We also find moderate evidence that the market bounces back after the initial drop. The point estimate for the second trading day after the game is 7.2 basis points for all soccer losses (controlling for first-order autocorrelation) and is statistically significant at close to 5% using a one-sided test. The point estimate is 5.6 basis points for elimination games and not statistically significant. These results are not reported for brevity but are available from the authors upon request.

[12] The professional soccer leagues of England, France, Germany, Italy, and Spain collectively account for 80% of soccer revenues in Europe, which in turn is by far the most dominant continent for global soccer income. These countries are known throughout the industry as the "Big Five." Together with Argentina and Brazil, these seven countries systematically occupy the top world rankings.

[13] This test is not reported in a table but is available from the authors upon request.

Table III

Abnormal Daily Stock Market Performance after International Soccer Matches for the Top Seven Soccer Nations

The table reports the ordinary least squares (OLS) estimates of β_W and β_L from

$$\tilde{\epsilon}_{it} = \beta_0 + \beta_W W_{it} + \beta_L L_{it} + u_{it},$$

where $\tilde{\epsilon}_{it}$ are the "abnormal normalized returns" defined in Section III.B and described in Table II. W_{it} is a dummy variable that takes the value one if country i wins a sports match on a day that makes t the first trading day after the match and zero otherwise, and L_{it} is a dummy variable for losses defined analogously. If games are mutually exclusive (such as elimination games, group games, and qualifying matches), W_{it} and L_{it} are vectors, where each element corresponds to a game type. In Panel A, the Top Seven soccer nations are Argentina, Brazil, England, France, Germany, Italy, and Spain. Panel B reports results for the remaining 32 soccer nations in our sample. The table reports results for soccer matches played over the period 1973 to 2004 in the World Cup, European Championship, Copa America, Asian Cup, World Cup qualifying stages, and European Championship qualifying stages. The reported t-statistics are computed by allowing the variance of u_{it} to be country specific (i.e., σ_i^2 is estimated for all countries) and by allowing for contemporaneous cross-country correlations (σ_{ij} is estimated for all pairs of countries).

	Wins			Losses		
	Number of Games	β_W	t-Values	Number of Games	β_L	t-Values
Panel A: Top Seven Soccer Nations						
All games	251	0.056	0.92	121	−0.217	−2.59
World Cup games	142	0.065	0.80	67	−0.374	−3.30
Continental cup games	109	0.044	0.48	54	−0.021	−0.17
Elimination games	101	0.148	1.55	52	−0.221	−1.70
Group games and close qualifiers	150	−0.006	−0.08	69	−0.213	−1.96
Panel B: Other Soccer Nations (32 Countries)						
All games	387	−0.067	−1.38	403	−0.139	−2.89
World Cup games	186	−0.102	−1.42	192	−0.183	−2.60
Continental cup games	201	−0.034	−0.51	211	−0.099	−1.50
Elimination games	76	−0.135	−1.26	86	−0.158	−1.54
Group games and close qualifiers	311	−0.050	−0.92	317	−0.134	−2.46

overstating the statistical significance of our estimates if the model does not fully capture the correlations among different countries' returns on a given date. For example, shocks to emerging markets are likely to be inadequately captured by the Datastream world index, which is mostly composed of returns from developed nations. To mitigate the problems created by time-clustering, we form "portfolios" of winners and losers for each game date. For each date t for which either $W_{it} = 1$ or $L_{it} = 1$ for some i, we average $\tilde{\epsilon}_{it}$ over all countries with $W_{it} = 1$, and average $\tilde{\epsilon}_{it}$ over all countries with $L_{it} = 1$. This yields two time series of abnormal normalized portfolio returns, $\hat{w}_{Lt}$ and $\hat{w}_{Wt}$, for losing

countries and winning countries, respectively. Under our null hypothesis, these time series should both have zero means.

Panel A of Table IV presents the number of win days and loss days, the average returns on the win and loss portfolios, and standard t-values for a test of zero mean. Consistent with all our earlier findings, there is a statistically significant loss effect as well as a negligible effect for wins. The point estimates are very similar to those in Panel B of Table II, aside from a small decrease in the statistical significance of the tests since we are dropping all cross-sectional information on a given day. However, the loss effect remains statistically significant at levels close to 5% or better for all final-stage game subsets (both elimination and group games). The results for the full sample of 524 losses, which is reduced to 358 date observations, remain highly significant, with a point estimate of −14.9 basis points and a t-statistic of −3.3.

We also investigate the sensitivity of our result to outliers. This test is motivated by Pinegar (2002), who shows that the clock change results of Kamstra

Table IV

Abnormal Daily Stock Market Performance after International Soccer Matches Using Portfolio Returns and Samples Trimmed of Outliers

Let $\tilde{\epsilon}_{it}$ be the "abnormal normalized returns" defined in Section III.B and described in Table II. For each date t for which either $W_{it} = 1$ or $L_{it} = 1$ for some i, we average $\tilde{\epsilon}_{it}$ over all countries with $W_{it} = 1$ and average $\tilde{\epsilon}_{it}$ over all countries with $L_{it} = 1$. This yields two time series of (normalized) portfolio returns, $\tilde{\epsilon}_{Lt}$ and $\tilde{\epsilon}_{Wt}$, for losing countries and winning countries, respectively. Panel A in the table reports the average over all dates of $\tilde{\epsilon}_{Lt}$ and $\tilde{\epsilon}_{Wt}$ under the mean column. In Panel A, column "N" reports the number of dates for which the above portfolios can be constructed. The t-statistics reported are obtained by using $SD(\tilde{\epsilon}_{jt})/\sqrt{N-1}$ as an estimate of the standard error of the mean. Panel B reports 10%-trimmed means of the residuals $\tilde{\epsilon}_{it}$. Observations for which variable L_{it} equals one and the residual is smaller than the 10th percentile or larger than the 90th percentile are removed from the sample. Observations for which W_{it} equals one are removed in a similar way. Compared to Table II this removes 20% of the sample. In Panel B, column "N" reports the number of games. The t-statistics for the trimmed means are based on standard asymptotic approximations to the distribution of trimmed means (Huber (1996)).

	Wins			Losses		
	N	β_W	t-Values	N	β_L	t-Values
Panel A: Portfolio Returns						
All games	389	−0.033	−0.79	358	−0.149	−3.33
Elimination games	113	−0.014	−0.18	96	−0.199	−2.15
Group games	137	0.038	0.56	125	−0.164	−2.19
Close qualifying games	155	−0.096	−1.37	149	−0.075	−1.10
Panel B: Trimmed Means						
All games	512	−0.020	−0.59	420	−0.126	−3.50
Elimination games	143	0.030	0.44	112	−0.156	−2.34
Group games	195	−0.026	−0.49	160	−0.164	−2.63
Close qualifying games	176	−0.050	−0.85	152	−0.065	−1.10

et al. (2000) are sensitive to outliers in their data. We define outliers as observations for which the dummy variables W_{it} or L_{it} equal one and the absolute value of the abnormal normalized returns, $\tilde{\epsilon}_{it}$, is "large." In other words, we identify observations with large negative or large positive returns on a win day or a loss day. Effectively, this approach identifies the observations that have the greatest influence on the estimates of β_W and β_L.

Panel B in Table IV reports trimmed means, where 20% of the game-day observations are removed (10% extreme negative observations and 10% extreme positive observations). The t-statistics reported are calculated using standard asymptotic approximations for trimmed means (see Huber (1996), Chapter 3). Again, we find that the loss effect documented in Table II is remarkably robust. After trimming the data, the point estimate after losses in international soccer matches is -12.6 basis points with a t-statistic of -3.50. The trimmed means for losses are slightly less negative than the untrimmed means, revealing that negative outliers tend to be somewhat larger in absolute value than positive outliers, especially for the qualifying games subset. However, both the economic and statistical significance of the results remain strong. Consistent with our previous analysis, these robust estimates fail to uncover any positive effect after wins.

E. Evidence from Other Sports

Panel B of Table II shows that the loss effect is statistically significant in all three mutually exclusive groups of the 524 soccer losses games (elimination, group, and close qualifiers). However, from Panel A of Table II, it is clear that the loss effect is strongest in the subsamples of 138 elimination games and 81 World Cup group games. To increase our sample of sports-related mood events, we investigate whether the loss effect documented for soccer exists in other international sports. To ensure that each sport is important in a reasonable number of countries, the sports we study are cricket, rugby, ice hockey, and basketball. The Appendix details country selection for each sport.

Since soccer is the main sport for the vast majority of the 39 countries we define as soccer nations, we expect that other sports will exhibit a weaker effect. A possible exception may be cricket, as this is the main sport for around half (India, Pakistan, Sri Lanka, and possibly South Africa) of the seven countries included as cricket nations. For example, approximately 75% of the sports-related advertising revenues in India are generated through cricket events, and the Indian government considered moving the 2004 elections to avoid a conflict with a cricket series against Pakistan, fearing a sporting defeat would severely impact electorate mood.

Table V reproduces the analysis in Tables II and IV for our sample of other sports. Somewhat surprisingly, given the lesser importance of these sports, Panel A of Table V shows a similar pattern to that reported for the soccer sample. In particular, the point estimate after losses in these other competitions is negative, -8.4 basis points, and statistically significant at conventional levels.

Table V

Abnormal Daily Stock Market Performance after International Cricket, Rugby, Ice Hockey, and Basketball Matches

The analysis is based on wins and losses for 24 countries (see the Appendix). The average time series has 5,081 trading days, which gives a total of 121,940 daily return observations. The table reports the ordinary least squares (OLS) estimates of β_W and β_L from

$$\tilde{\epsilon}_{it} = \beta_0 + \beta_W W_{it} + \beta_L L_{it} + u_{it}, \tag{6}$$

where $\tilde{\epsilon}_{it}$ are the "abnormal normalized returns" defined as in Section III.B. W_{it} is a dummy variable that takes the value one if country i wins a sports match on a day that makes t the first trading day after the match and zero otherwise, and L_{it} is a dummy variable for losses defined analogously. If games are mutually exclusive (cricket games, rugby games, etc.), W_{it} and L_{it} are vectors, where each element corresponds to a game type. The table reports results for One Day International cricket matches played over the period 1975 to 2004; Six Nations, Tri Nations, and World Cup rugby matches played between 1973 and 2004; World Championships (1998 to 2004), Olympics (1980 to 2002), and World Cup/Canada Cup (1996 and 2004) ice hockey matches, and Olympics (1992 to 2004) and World Championships (1994 to 2002) basketball matches. The Appendix details the country selection for each sport. Panel A reports the estimates using the full cross-section of countries. The t-statistics are computed by allowing the variance of u_{it} to be country specific (i.e., σ_i^2 is estimated for all countries) and by allowing for contemporaneous cross-country correlations (σ_{ij} is estimated for all pairs of countries). Panels B and C replicate the analysis in Table IV for the data on these four other sports. In Panels A and C, column "N" reports the number of games. In Panel B, column "N" reports the number of dates for which there is a least one win (left side of the table) or at least one loss (right side of the table).

	Wins			Losses		
	N	β_W	t-Value	N	β_L	t-Value
Panel A: Abnormal Returns						
All games	903	−0.013	−0.39	645	−0.084	−2.21
Cricket	153	−0.057	−0.73	88	−0.187	−1.85
Rugby	403	−0.086	−1.73	307	−0.095	−1.74
Ice hockey	238	0.105	1.57	148	0.083	1.02
Basketball	111	0.071	0.74	102	−0.208	−2.11
Panel B: Abnormal Portfolio Performance						
All games	503	−0.073	−1.68	442	−0.083	−1.88
Cricket	99	−0.146	−1.08	70	−0.331	−2.26
Rugby	275	−0.123	−2.23	257	−0.087	−1.55
Ice hockey	106	0.099	1.30	89	0.125	1.50
Basketball	40	0.061	0.73	42	−0.101	−1.06
Panel C: Trimmed Means						
All games	723	0.019	0.66	517	−0.088	−2.53
Cricket	123	0.031	0.50	72	−0.301	−3.02
Rugby	323	−0.058	−1.25	247	−0.083	−1.65
Ice hockey	192	0.112	1.99	120	0.079	1.08
Basketball	89	0.067	0.93	82	−0.167	−1.91

The effect is negative for all subsamples but ice hockey, and is particularly large for cricket and basketball. As for soccer, there is no significant effect after wins in the overall sample. Although smaller in magnitude compared to the soccer point estimates from Table II (consistent with the other sports being a weaker mood variable), the data support the hypothesis that these other sporting events are also associated with stock market movements.

The last two panels of Table V perform robustness checks along the lines of those in Section III.D. The point estimate for the full sample of games is virtually unchanged by either pooling the cross-sectional returns over dates (Panel B) or computing trimmed means (Panel C). The t-statistic drops to -1.88 for the portfolio approach and increases to -2.53 for trimmed means. The cricket subsample is the most robust of the four, showing even larger point estimates and stronger statistical significance using either portfolio returns or trimmed means, partly because the trimming removes an extreme positive outlier for India after a cricket loss.[14] This finding is consistent with the fact that cricket is the number one sport, and therefore a strong mood proxy, in half of the seven countries included as cricket nations. The evidence is marginal for the rugby and basketball subsamples, and only the ice hockey games do not seem to have point estimates consistent with our previous analysis. Again, this could be related to the fact that these sports are second in importance when compared to soccer, implying that a smaller proportion of the population is influenced by game outcomes.

To sum up, the results reported in Tables II through V show a striking loss effect. Stock markets exhibit a statistically and economically significant negative return on days after a loss by the national team in a sport the country views as important. The effect is especially strong after international soccer losses but is also significant after losses in other sports. The following section investigates competing interpretations of the loss effect.

IV. Soccer, Mood, and Economics

Our study is motivated by the behavioral alternative hypothesis that soccer results affect stock returns through their impact on investor mood. However, the loss effect may be a result of efficient markets rationally reacting to the negative economic consequences of losing a game. This includes direct economic effects such as lower sales of related merchandise and advertising, the negative impact on productivity, and a potential reduction in consumer expenditure resulting from mood changes. The main goal of this section is to distinguish between these competing explanations for the loss effect. One simple argument that casts doubt on a pure economic explanation is the sheer size of the effect. To

[14] On March 3, 1992, the stock market index for India rose 29%. This can be attributed to a market deregulation that authorized foreign institutional investors to make investments in all securities traded on the primary and secondary markets. The Indian cricket team experienced a loss on March 1; since March 2 is coded as a holiday for India, March 3 is the first trading day after the cricket game.

put the results in perspective, 40 basis points of the U.K. market capitalization as of November 2005 is $11.5 billion. This is approximately three times the total market value of all the soccer clubs belonging to the English Premier League.

We further investigate the competing explanations for the loss effect in three ways. First, rational asset pricing suggests that market declines should be particularly strong for losses that are unexpected under objective probabilities. To test this implication we add data on the ex ante probability of a win in a particular game. Second, we study whether the effect is stronger in small versus large stocks since the former are held more by local investors and their valuations are more likely to be affected by sentiment. Third, we study trading volume around our event dates to rule out potential stock market liquidity effects.

A. The Loss Effect and Expected Game Outcome

Even if the negative effect of a soccer loss is due to irrationality, investors could still be perfectly rational when pricing financial assets. In particular, market efficiency predicts that investors should price in the expected economic impact of soccer results before the game. Therefore, the loss effect should be stronger for losses that are more unexpected. To test this conjecture, let V_{Wit} denote the value of the stock market in country i at time t following a soccer win, and let V_{Lit} denote the corresponding value after a loss. A negative economic effect of soccer losses suggests that $V_{Wit} > V_{Lit}$.

If investors have assigned a probability p_{it} to a national team win, the economic effect priced into the index level of the national stock market will be $p_{it}V_{Wit} + (1 - p_{it})V_{Lit}$. Let I_{it} be the index level that includes the expected soccer effect. After controlling for other factors that move the national index, the soccer-related realized return on the index is

$$\epsilon_{it} = \frac{(V_{Wit} - V_{Lit})}{I_{it}} W_{it} - \frac{(V_{Wit} - V_{Lit})}{I_{it}} p_{it} + v_{it}, \tag{3}$$

where W_{it} is a dummy variable that equals one (zero) if country i wins (loses) a soccer match on a day that makes t the first post-game trading day, and v_{it} is a mean zero error term.

We can generate testable predictions of a rational story as follows. Since the index level I_{it} is large relative to the soccer effect, $\partial I_{it}/\partial p_{it}$ is approximately zero. This implies that $\partial \epsilon_{it}/\partial p_{it}$ is approximately equal to $-(V_{Wit} - V_{Lit})/I_{it}$. Thus, if we study returns on game dates only, the soccer-related realized return can be written as a cross-sectional regression:

$$\epsilon_{it} = \alpha_0 + \alpha_1 W_{it} + \alpha_2 p_{it} + v_{it}. \tag{4}$$

Comparing equation (4) to equation (3), the above economic arguments imply the following three restrictions on the parameters: $\alpha_0 = 0$, $\alpha_1 > 0$, and $\alpha_1 = -\alpha_2$.

While the above arguments clearly predict a more negative impact of an unexpected loss (i.e., $\alpha_2 < 0$), there are no unambiguous predictions under

the behavioral explanation. First, as we discuss in Section I, the allegiance bias suggests that agents' beliefs may not be closely related to expectations computed under objective probabilities. That is, under an allegiance bias, losses are nearly always unexpected. For example, 86% of fans surveyed thought that England would beat Brazil in the 2002 World Cup quarter final, even though Brazil was the world's top-ranked team; this contrasts with the 42% probability that bookmakers assigned to a victory (Brazil eventually won the competition). Second, even if data on subjective probabilities were available, it is not clear that we would expect a negative coefficient on the subjective probability in equation (4). On the one hand, losses to strong opponents may be less painful as they are less unexpected. On the other hand, formidable opponents tend to be historic rivals and so a loss against them (e.g., England losing to Germany or Spain to Italy) may be as emotionally painful as an "embarrassing" loss to weak opposition.

We test the restrictions on the coefficients of equation (4) using probabilities derived from Elo ratings. Let E_H and E_A be the Elo rating for the "home team" and the "away team," respectively. The probability that the home team wins is[15]

$$\mathbb{P}(\text{Home-team wins}) = \frac{1}{10^{-(E_H+100-E_A)/400}+1}. \tag{5}$$

The probabilities implied by the Elo ratings have a correlation of 0.929 with betting odds data that we obtain for slightly less than 60% of the overall sample. Evidence surveyed in Hausch and Ziemba (1995) shows that odds data coincide closely with objective probabilities, implying that our Elo-based ex ante probabilities should proxy well for expected game outcomes.

The estimation of equation (4) is conducted in two stages. First, we estimate $\tilde{\epsilon}_{it}$ as described in Section III.B. Second, the game date residuals from the first-stage regression are used as the dependent variable in the cross-sectional regression in equation (4).

Panel A of Table VI reports the results from the estimation of equation (4) without any restrictions on the coefficients. To ensure that point estimates in Panel A are comparable to our earlier findings, we normalize p_{it} to have zero mean. Thus, since W_{it} is zero on loss days, the intercept picks up the loss effect controlling for the ex ante probability that country i will win the match. Focusing first on the sample of all games, the intercept is negative, close to the point estimate for losses from Table II, and is statistically significant. The effect after wins can be computed by summing the coefficient estimates for α_0 and α_1. This sum is close to zero, confirming our earlier findings. In the last column of Panel A, we observe that there seems to be no relationship between

[15] For the games for which there is no home team (i.e., most final-stage games), we use

$$\mathbb{P}(\text{Team H wins}) = \frac{1}{10^{-(E_H-E_A)/400}+1}.$$

Table VI

Predicted Outcomes and Abnormal Daily Stock Market Performance after International Soccer Matches, 1993 to 2004

The table reports the ordinary least squares (OLS) estimates for the model

$$\tilde{\epsilon}_{it} = \alpha_0 + \alpha_1 W_{it} + \alpha_2 p_{it} + v_{it},$$

where $\tilde{\epsilon}_{it}$ is the error term from estimating equation (1) without the soccer dummy variables and using normalized stock index returns, W_{it} is a dummy variable that equals one if country i wins a soccer match on a day that makes t the first trading day after the match and zero if a game is lost, p_{it} is the ex ante probability that country i wins the game, and v_{it} is an error term with mean zero and variance σ_v^2. The analysis is based on 39 countries (see the Appendix). The sample period is January 1993 through November 2004. Panel A reports results for matches played in the World Cup. Panel B reports results for matches played in the World Cup, the European Championship, the Asian Cup, and Copa America. The probabilities p_{it} are computed using Elo ratings employing the methodology detailed in Section IV.A. Elimination matches are matches in which the loser is eliminated from further play in the tournament. The parentheses contains t-statistics. The last column reports the Kodde and Palm (1986) Wald test statistic for the test of a null hypothesis that involves inequality restrictions.

	Number of Games	α_0 (t-Value)	α_1 (t-Value)	α_2 (t-Value)	Wald-D (p-Value)
Panel A: Unrestricted Model					
All games	1,118	−0.162 (−3.06)	0.142 (2.18)	−0.004 (−0.03)	
Elimination games	297	−0.192 (−1.97)	0.223 (1.88)	0.041 (0.13)	
Group games	420	−0.195 (−2.18)	0.153 (1.33)	−0.041 (−0.17)	
Close qualifying games	401	−0.110 (−1.16)	0.077 (0.72)	0.005 (0.01)	
Panel B: Restricted Model					
All games	1,118		0.138 (2.11)	−0.138 (−2.11)	9.274 (0.018)
Elimination games	297		0.215 (1.81)	−0.215 (−1.81)	2.643 (0.358)
Group games	420		0.150 (1.30)	−0.150 (−1.30)	5.263 (0.112)
Close qualifying games	401		0.074 (0.69)	−0.074 (−0.69)	2.007 (0.469)

ex ante probabilities and stock market reactions. Thus, the main implication of models that assume rational investors is not borne out in our data.

To further test this implication, Panel B of Table VI reports results from the estimation of the model in equation (4) under the restricted parameters. Since the model implies both equality and inequality restrictions, we estimate the model using quadratic programming. In particular, we estimate the model under the parameter restrictions above and we test the null hypothesis that these restrictions jointly hold against the alternative hypothesis that the restrictions do not hold. Kodde and Palm (1986) develop a Wald test for joint equality and inequality restrictions. The last column of Table VI reports the Kodde-Palm "Wald-D" test statistic. For all games taken together the Wald-D statistic is 9.274. Under the null, the probability of observing a Wald-D statistic of 9.274 or larger is 0.018.

The fundamental reason the economic explanations are rejected in our data is that the loss effect picked up by the intercept in equation (4) is too large to be explained by the win probability. To see this, consider a model in which investors are rational. This implies that $E(W_{it})$ should be identical to p_{it}, and thus the average number of wins in the sample (i.e., the average of W_{it}) should converge to the average p_{it} as the sample size increases. Since the large soccer nations are overrepresented in our sample, the average p_{it} is 0.62. One immediate implication of this result is that the loss effect should be of opposite sign, and approximately $0.62/0.38 = 1.6$ times the magnitude, of the win effect. This implication has already been rejected by the evidence in Table II, which shows that the loss effect is 13 times as large as the win effect.

B. Portfolio Characteristics and Local Ownership

To the extent the mood of local investors drives our results, we would expect stocks with especially high local ownership to be more sensitive to soccer results. The models of Merton (1987) and Gehrig (1993) predict that foreigners underweight stocks for which their informational disadvantages are greatest. It seems reasonable to believe that foreigners are at a greater informational disadvantage in small stocks, which have low analyst and media coverage (Bhushan (1989)), and in growth firms, where "hard" accounting information is a less important driver of firm value. This prediction finds support in Kang and Stulz (1997) and Dahlquist and Robertsson (2001), who document that small firms are underweighted by foreign investors in Japan and Sweden, respectively. Dahlquist and Robertsson (2001) also find that foreigners prefer firms with large cash positions on their balance sheets, which is a feature of value stocks. Moreover, even holding local ownership constant, investor sentiment is more likely to affect small stocks as they are disproportionately held by individual investors (Lee, Shleifer, and Thaler (1991)) and are less interesting to potential arbitrageurs who would act to eliminate any mispricing. Indeed, many market "anomalies," such as the January and Monday effects are stronger in small stocks, and Baker and Wurgler (2006) find that small stocks are more strongly affected by investor sentiment. Hence, differences in both the extent of local ownership and the effect of sentiment given a particular ownership structure lead to the cross-sectional prediction that soccer results should have a greater effect on a small stock index than a large stock index, and on a growth index than a value index.

Panel A of Table VII reports the results from estimating the model in equation (2) using pairs of small/large or value/growth indices. The Appendix describes our index selection. The results show that the loss effect is stronger in small-cap indices. The point estimate after losses is -0.245 basis points, two-and-a-half times the estimate of -0.093 for large-cap indices. The -15.2 basis point difference is statistically significant at below the 10% level using a one-sided test. By contrast, the loss effect is of the same magnitude in both value and growth indices. The value-growth loss effect is the same as the effect for the overall market index. Thus, the result could possibly be explained

Table VII
Abnormal Daily Stock Market Performance after International Soccer Matches for Size Sorted Portfolios and Value-Growth Sorted Portfolios, 1990 to 2004

The table reports the ordinary least squares (OLS) estimates of β_W and β_L from

$$\tilde{\epsilon}_{it} = \beta_0 + \beta_W W_{it} + \beta_L L_{it} + u_{it}, \tag{7}$$

where u_{it} is an error term that is allowed to be contemporaneously correlated between countries, W_{it} is a dummy variable that takes the value one if country i wins a soccer match on a day that makes t the first trading day after the match and zero otherwise, and L_{it} is a dummy variable for losses defined analogously. $\tilde{\epsilon}_{it}$ are the "abnormal normalized returns" defined in Section III.B and described in Table II, where the stock market indices are now a large-cap index, small-cap index, growth index, or a value index. The small indices are those provided by HSBC via Datastream for the list of 18 countries for which we have a large index (see the Appendix for details). The growth and value indices are from Standard and Poor's, both available from Datastream for 34 out of the 39 countries in Table AI.

	Wins			Losses		
	Number of Games	β_W	t-Values	Number of Games	β_L	t-Values
Small stocks	243	−0.141	−2.50	157	−0.245	−3.32
Large stocks	243	−0.007	−0.12	157	−0.093	−1.33
Test of difference		−0.134	−1.67		−0.152	−1.50
Growth stocks	391	−0.096	−2.10	290	−0.149	−2.83
Value stocks	391	−0.085	−1.64	290	−0.141	−2.58
Test of difference		−0.011	−0.16		−0.008	−0.10

by foreigners having equal access to the individual firms that constitute the value-growth indices.

C. Liquidity

This section investigates whether the loss effect is driven by changes in liquidity. If investors are "hung over" on the day after a match, they may not want to participate in the stock market that day, causing a reduced order flow. If sufficiently many local investors stay away from the market, the greater execution time for a trade may induce sellers to accept a lower price. To investigate the liquidity hypothesis, we use data on aggregate trading volume on the stocks in the national index.

To measure abnormal trading volume, we model expected volume using a filtering procedure similar to the one in Gallant, Rossi, and Tauchen (1992). In particular, expected volume is constructed in the following way. Let V_{it} be the log of aggregate trading volume for the constituent shares of country i's stock index (from Datastream). We run the regression $V_{it} = \gamma_{0i} x_{it} + u_{it}$, where x_{it} is a set of explanatory variables. Next, we estimate variance according to $\log(\hat{u}_{it}^2) = \gamma_{1i} y_{it} + \epsilon_{it}$, where y_{it} is a second set of explanatory variables. Finally,

Table VIII

Abnormal Trading Volume after International Soccer Matches

The table reports the ordinary least squares (OLS) estimates of β_W and β_L from

$$\hat{w}_{it} = \gamma_0 + \beta_W W_{it} + \beta_L L_{it} + u_{it},$$

where $\hat{w}_{it}$ is abnormal volume constructed in a way that follows Gallant, Rossi, and Tauchen (1992). Specifically, let V_{it} be the log of aggregate trading volume for the constituent shares of country i's stock index (from Datastream). Run the regression $V_{it} = \gamma_{0i} x_{it} + u_{it}$, where x_{it} is a set of explanatory variables. Next, estimate variance according to $\log(\hat{u}_{it}^2) = \gamma_{1i} y_{it} + \epsilon_{it}$, where y_{it} is a second set of explanatory variables. Finally, define $\hat{w}_{it} = a_i + b_i \hat{u}_{it}/\exp(\hat{\gamma}_i y_{it}/2)$, where a_i and b_i are chosen so that $\hat{w}_{it}$ has zero mean and unit variance. For the volume regressions, x_{it} include day-of-the-week and month dummies, two lags of volume, a time trend, and the time trend squared. For the variance equation, y_t includes the variables in x_{it} except the two lags of volume. Elimination matches are matches for which the loser is eliminated from further play in the tournament. The sample includes all countries for which Datastream provides volume data, which leaves us with a sample of 34 countries. Compared to the 39 countries in Table AI, the missing countries are Bahrain, Croatia, Jordan, Nigeria, and Saudi Arabia. For most countries Datastream volume data do not start until the beginning of the 1980s. The t-statistics are computed by allowing the variance of u_{it} to be country specific, and u_{jt} and u_{it} to be contemporaneously correlated.

	Wins			Losses		
	Number of Games	β_W	t-Values	Number of Games	β_L	t-Values
All games	449	−0.045	−0.90	379	−0.018	−0.33
Elimination games	109	0.026	0.23	97	0.149	1.41
Group games	191	−0.119	−1.54	160	−0.133	−1.64
Close qualifying games	149	−0.001	−0.02	122	0.001	0.01

we define $\hat{w}_{it} = a_i + b_i \hat{u}_{it}/\exp(\hat{\gamma}_i y_{it}/2)$, where a_i and b_i are chosen so that $\hat{w}_{it}$ has zero mean and unit variance. For the mean volume regression, x_{it} includes day-of-the-week and month dummies, two lags of volume, a time trend, and the time trend squared. For the variance equation, y_t includes the variables in x_{it} except the two lags of volume. The procedure essentially generates, for each country, a mean zero time series of abnormal volume with unit variance. The normalization of all the time series eliminates the heterogeneity in volatility across countries. The effect of soccer match outcomes on volume is estimated using the model $\hat{w}_{it} = \gamma_0 + \beta_W W_{it} + \beta_L L_{it} + \epsilon_{it}$.

The sample includes 34 countries from the original sample for which Datastream provides volume data.[16] For most countries Datastream volume data do not start until the beginning of the 1980s, which reduces the number of soccer matches that can be included in the sample. Table VIII reports results using the abnormal volume time series. If the loss effect is caused by a reduction in market liquidity on the days after a soccer game, we would expect to see a reduction in volume on these days. For elimination games, the point estimates are positive

[16] Compared to the 39 countries in Table AI, the missing countries are Bahrain, Croatia, Jordan, Nigeria, and Saudi Arabia.

but insignificant for both wins and losses. For the sample of all games, the point estimates of abnormal volume are all negative but again insignificant. Thus, there does not seem to be any reliable decrease in volume on the loss days. We therefore conclude that the loss effect is not related to a reduction in market liquidity, at least when liquidity is measured using trading volume.

By contrast, under a behavioral story there are no clear predictions as to the effect of mood changes on volume. Although one might expect a bad mood to cause inactivity and inertia in traders, it is equally plausible that investors may trade more to take their minds off the soccer defeat. Indeed, there is ample psychological evidence that agents engage in "mood regulation," taking actions to fix their mood. For example, Erber and Tesser (1992) note that "exerting effort on a task may be one way to successfully overcome sad moods" and find evidence that a negative mood is attenuated by performing challenging tasks. Trading is a plausible example of such a task: Not only is it a cognitively intense activity, but it also has the potential of generating profits to negate the negative mood.

V. Conclusion

Motivated by the abundance of psychological evidence showing that sports results have a strong effect on mood, this paper investigates the stock market effect of international soccer results. We document a strong negative stock market reaction to losses by national soccer teams. The size of the loss effect is economically significant—in monthly terms, the excess returns associated with a soccer loss exceed 7%. We find a statistically significant but smaller loss effect for international cricket, rugby, and basketball games. There is no evidence of a corresponding reaction to wins in any of these sports.

The finding that the effect is not priced into the index when a loss is highly expected leads us to reject the view that the loss effect stems from the reaction of rational investors to cash flow relevant information. Instead, we interpret the effect as resulting from the impact of sports results on investor mood. There are several justifications for this interpretation. First, soccer results have been demonstrated to impact mood but have little direct economic impact. Second, the effect is more pronounced in countries where soccer is especially important, for games in the World Cup, and for elimination games. These important matches are precisely the games with greatest mood impact. Third, the effect is especially large in small stocks. Small stocks have been previously found to be especially sensitive to investor sentiment, and are predominantly held by local investors, whose mood is affected by the performance of the national soccer team.

The magnitude of the loss effect, and its concentration in Western European countries with developed stock markets, suggests that investors may obtain large excess returns by trading on these mood events, for instance, by shorting futures on both countries' indices before an important match to exploit the asymmetry of the effect. However, the events we cover do not occur with enough frequency to justify a portfolio fully dedicated to trading on them. Moreover,

because the effect seems to be particularly strong in small stocks and involves shorting, even traders who face low transaction costs would find it challenging to take advantage of the price drop. Our principal contribution is not to identify a profitable trading strategy, however, but to document that mood can have a large effect on stock returns. In light of our findings, this paper significantly expands the existing evidence linking mood to asset prices.

Appendix

A. Stock Index Returns and Index Volume

Returns are obtained from Datastream, and are computed using a total return index (assuming that dividends are reinvested). If the total return index is unavailable, we use a price index instead. Index returns are measured in the local currency. The starting date of the index for country i is selected to ensure that the market is reasonably liquid at the time of the starting date. The starting date is the first date for which the 5-day average number of firms in the index is at least 10 and the average number of firms (over a 5-day period) that experienced a price change is greater than 50%.

We use the total return indices with a Datastream mnemonic that starts with "TOTMK." Datastream does not provide TOTMK indices for seven countries in our sports data. For Croatia, Slovakia, and Lithuania we use the Nomura price index. For Bahrain, Jordan, Nigeria, and Saudi Arabia we use the S&P/IFCG indices from Standard & Poor's Global Index Series. The index returns for Argentina, Czech Republic, Indonesia, Poland, Romania, and Russia are very volatile and contain extreme returns in the first few months of the series. Based on a visual inspection we trim the beginning of these time series. Only four basketball wins are lost because of this trimming. The return time series for South Korea, Indonesia, and Nigeria exhibit a persistent and dramatic increase in volatility in September 1997, August 1997, and April 1999, respectively. Whenever we use these time series in our analysis, we include a dummy variable that takes the value one before these dates and zero otherwise. None of our reported results are influenced by the trimming or the inclusion of the time dummies. The second column of Table AI reports the starting date for the returns time series.

For the analysis in Table VII we use data on large indices for 18 countries out of the 39 soccer countries listed in Table AI. Namely, we include as large-cap indices the Australia ASX-20, Austria ATX Prime, Belgium BEL-20, Denmark Copenhagen KFX, England FTSE-100, France CAC-40, Germany DAX-30, Greece Athens SE General, Ireland ISEQ, Italy Milan Comit-30, Japan Nikkei-225, Netherlands AEX, Norway OBX, Portugal PSI-20, South Korea Kospi-200, Spain IBEX-35, Sweden OMX-30, and Switzerland MSCI. The small indices are those provided by HSBC via Datastream for the list of countries for which we have a large index. The growth and value indices are from Standard and Poor's, both

Table AI

Mean Daily Percent National Index Return and Number of Wins and Losses in International Team Sport Matches

Country	Time Series Begins	Mean Log Return	Soccer		Cricket		Rugby		Ice Hockey		Basketball	
			W	L	W	L	W	L	W	L	W	L
Argentina	19900108	0.124	28	16							15	9
Australia	19730109	0.047	5	9	40	16	54	46				
Austria	19830427	0.056	8	11								
Bahrain	20000503	0.050	4	3								
Belgium	19730109	0.042	30	31								
Brazil	19940711	0.072	37	7							5	16
Canada	19730109	0.041							47	17	8	8
Chile	19890711	0.089	12	24								
China	19930706	0.026	9	11							7	21
Colombia	19920116	0.061	30	17								
Croatia	19960412	0.055	12	9								
Czech Republic	19940315	0.019	8	7					39	13		
Denmark	19820108	0.051	27	23								
England	19730102	0.050	25	26	31	17	97	58				
Finland	19880406	0.046							42	17		
France	19730109	0.050	42	20			109	46			3	3
Germany	19730109	0.031	54	19					9	28	8	4
Greece	19880112	0.073	12	12							11	8
India	19900109	0.071			18	14						
Indonesia	19900410	0.019	1	8								
Ireland	19780111	0.061	14	15			54	74				
Italy	19730109	0.050	45	18			8	35			10	7
Japan	19730110	0.020	21	14								
Jordan	19950707	0.064	2	2								
Lithuania	19960111	0.034									14	7
Mexico	19880415	0.107	22	16								
Netherlands	19730109	0.043	43	28								
New Zealand	19880210	0.042			19	12	54	23				
Nigeria	19950706	0.096	2	4								
Norway	19800221	0.049	8	11								
Pakistan	19920723	0.052			11	8						
Peru	19940201	0.045	12	17								
Poland	19940308	0.010	3	7								
Portugal	19900123	0.027	15	9								
Romania	19970509	0.085	5	6								
Russia	19940726	0.102	7	10					21	16	12	8
Saudi Arabia	19980102	0.091	5	8								
Slovakia	19970402	0.019							25	16		
South Africa	19730109	0.072	3	2	19	10	27	25				
South Korea	19870916	0.028	20	15								
Spain	19870309	0.043	20	15							18	11
Sri Lanka	19900424	0.049			15	11						
Sweden	19820112	0.061	17	17					41	19		
Switzerland	19730202	0.032	16	17					14	22		
Thailand	19870112	0.051	1	11								
Turkey	19880112	0.212	12	13								
Venezuela	19930126	0.115	1	16								
All countries		0.056	638	524	153	88	403	307	238	148	111	102

available from Datastream for 34 out of the 39 soccer countries listed in Table AI. Owing to data limitations with the return series, we use the price series for all of these indices.

Datastream uses the same calendar for all countries and does not provide information about holidays. To avoid computing returns for holidays, we identify holidays as days on which the price of fewer than three of the stocks in the index moved and there was no trading volume. This procedure identifies more than 95% of the holidays. We identify the remaining holidays using the same two criteria separately.

Volume data are available for all countries for which Datastream provides a TOTMK index. For some countries, the volume data contain multiple zero-volume days at the beginning of the time series. We set the start date of the time series as the first date on which volume exceeds 100 for five consecutive days.

B. Soccer

We obtain international soccer results from 1973 through 2004 from the web site www.rdasilva.demon.co.uk. We manually check the data for errors using various sources, including the websites of the Fédération Internationale de Football Association (FIFA) and the Union des Associations Européennes de Football (UEFA).

To enter our sample, Datastream must provide a national stock market index with daily returns and a country needs to be recorded with at least one win or one loss (over the time period for which we have return data) in either the World Cup or the continental cups. These criteria result in a sample of 41 countries. However, given the large number and strong popularity of club sports (baseball, basketball, American football, and ice hockey) in Canada and the United States, these countries are excluded. Table AI lists the 39 countries that are included.

In the 1974 and 1978 World Cups, eight teams proceeded from the group stage to a second-round playoff series. The winner and runner-up from this playoff stage qualified for the final. We define all games in the second-round series as elimination games. A similar format was used in the 1982 World Cup, but 12 teams proceeded to the second round and the four top teams played in the semi-finals. For this year we also define the second-round games as elimination games.

C. Cricket

Traditionally, cricket is played over multiple days (with a maximum of five). This does not lend itself easily to a study that relates game outcome to stock market response because it is not obvious when the outcome of the game became clear. However, since cricket is the main sport in many South Asian countries, we include One Day International (ODI) cricket matches in our sample of other sports. The International Cricket Council (ICC) World Championship is played as ODIs and we collect game results for eight World Championships played

between 1975 and 2003. We obtain the cricket results from the website of the ICC, www.icc-cricket.com. We define as cricket nations those that were ranked in the top 10 countries every year between 2002 and 2005 (the top 10 do not change over this period). When we restrict the sample countries to those that have stock market data on Datastream, we are left with seven cricket nations: Australia, England, India, New Zealand, Pakistan, South Africa, and Sri Lanka. Table AI reports the number of cricket wins and losses.

D. Rugby

We obtain international rugby data from the web site www.rugbyinternational.net. Data for Australia from 2001 and for South Africa were unavailable from the web site owing to a broken link and were obtained directly from the web site owners. We study all games in the Six Nations, Tri Nations, and the final stages of the World Cup. Rugby nations are defined as the countries that participate in the Tri Nations (Australia, New Zealand, and South Africa) or Six Nations (England, Wales, Scotland, Ireland, France, and Italy). Scotland and Wales are excluded because they have no independent stock market, leaving us with seven rugby nations. Table AI reports the number of rugby wins and losses.

E. Ice Hockey

We collect ice hockey data from the web site www.iihf.com of the International Ice Hockey Federation (IIHF) and the independent web site www.hockeynut.com. The hockey matches consist of the World Championships (1998 to 2004), Olympics (1980 to 2002), and World Cup/Canada Cup (1996 and 2004) competitions. We define ice hockey nations as the top 10 countries based on performance in the 2004, 2003, 2002, and 2001 World Championships and the 2002 Olympics. As for soccer, the United States is excluded: Not only does hockey lag behind baseball, American football, and basketball, but also any hockey interest is focused on the National Hockey League rather than international matches (the NHL playoffs occur at the same time as the World Championships, meaning many top players do not participate in the latter). Latvia is excluded because of no stock market data. This leaves us with the following eight hockey nations: Canada, Czech Republic, Finland, Germany, Russia, Slovakia, Sweden, and Switzerland. Table AI reports the number of ice hockey wins and losses.

F. Basketball

We obtain World Championship and Olympic basketball results from www.fiba.com. The web site contains, for each tournament, the names of the two opponents, the round, and the result. Unfortunately it does not contain dates, so these have to be obtained from a variety of other sources. Olympic dates are obtained from sports.espn.go.com/oly/index for

2004 and 2000, and www.sunmedia.ca/OlympicsBasketball/sked.html for 1996. World Championship dates are obtained from www.insidehoops.com/wbc.shtml for 2002 and the Associated Press headlines for 1998; see amarillo.com/sports/index080498.html as an example of headlines for a particular day. For the 1992 Olympics and the 1994 World Championships, the U.S. dates are obtained from www.usocpressbox.org. Since games in each round take place on the same day, we could then work out the dates for all other teams' matches for the entire 1994 World Championships and the quarter-finals onward for the 1992 Olympics.

To define basketball nations, we follow the same approach as for soccer and require that a country participated in a significant number of basketball events. This requirement eliminates Japan, Turkey, Venezuela, South Korea, Croatia, and Nigeria. A total of 27 games are lost because of this requirement. We also remove Australia and New Zealand because at least two other sports (cricket and rugby) are more important in terms of attention in these countries. Again, we remove the United States owing to the substantially greater focus on club sports and college basketball. Many top American NBA players do not participate, in contrast to other countries, which are at close to full strength. This is consistent with the limited media coverage of international basketball in the United States. These removals leave us with 11 basketball nations: Argentina, Brazil, Canada, China, France, Germany, Greece, Italy, Lithuania, Russia, and Spain. Table AI shows the number of basketball wins and losses for these 11 countries.

G. Multiple Games on One Day

If a country plays an international game in more than one of the sports (soccer, cricket, rugby, ice hockey, and basketball) on a single day, we remove the observation if the country wins in one sport and loses in another. If the outcome is the same in all sports, we keep the observation. For example, England won a cricket match and a rugby match on February 17th and 24th, 2003. All four of these observations are kept. This adjustment affects less than 1% of our sample of games.

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