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 −38 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.

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1 Introduction

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 that the loss effect after soccer games is driven by economic factors such as reduced productivity or lost revenues. We also document that the effect is stronger in small stocks, which have previously been found to be 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 investigating the asset pricing impact of behavioral biases documented in psychology research. This literature has expanded significantly over the last decade and 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 have been to link returns either to a single event or a continuous variable that impacts mood. Examples of a continuous variable are sunshine (Saunders (1993); Hirshleifer and Shumway (2003)), temperature (Cao and Wei (2005)), daylight (Kamstra, Kramer, and Levi (2003)), and lunar cycles (Yuan, Zheng, and Zhu (2005)). The event study approach is used by Kamstra, Kramer, and Levi (2000) to investigate the impact of disruption to sleep patterns caused by changes to and from daylight saving and by Frieder and Subrahmanyam (2004) to study non-secular holidays. The main advantage of the event approach compared to the use of a continuous variable is that it clearly identifies a sudden change in the mood of investors. As for all event studies, this gives a large signal-to-noise ratio in returns. The main disadvantage is that the number of observed signals tends to be low, reducing statistical power.

Our main contribution is to study a variable, international soccer results, that has particularly attractive properties as a measure of mood. Extensive psychological evidence, reviewed 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

[1]Several countries even legally 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.

substantial and correlated mood swings in a large proportion of a country's population. These characteristics give us a strong *a priori* motivation for using game outcomes to capture mood changes among investors. This is a key strength of our study since it mitigates concerns about "data mining."

The large loss effect that we report reinforces the findings of Kamstra, Kramer, and Levi (2000) who document a stock market effect of similar magnitude related 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 other robustness checks. Another contribution of this paper is that we are able to go a long way towards addressing the main disadvantage of the event approach. Our sample of soccer matches exceeds 1,100 observations, and exhibits a significant cross-sectional variation across nations. In addition, we study more than 1,500 cricket, rugby, ice hockey, and basketball games.[2] The sample of 2,600 independent observations compares favorably to existing mood-event studies.

The rest of the paper is organized as follows. Section 2 explains the *a priori* motivations for investigating the link between sports and stock returns. In Section 3 we describe the data, and in particular the competitions that are the subject of our study. Section 4 documents an economically and statistically significant loss effect. Section 5 distinguishes between behavioral and economic explanations for this effect. Section 6 summarizes our findings and concludes.

2 Motivation

A number of recent papers have documented a link between mood and stock returns. Convincing arguments that such results are not simply the product of "data mining" are either a strong *a priori* reason 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). Moreover, since the null hypothesis is that markets are efficient, the investigation should include a clear unidirectional alternative hypothesis. This limits the possibility of rejecting the null in any direction to suggest statistical significance. 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 would be expected with certain religious holidays and negative returns with others.

[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 the effect of wins and losses is symmetric and 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.

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, it must drive mood in a substantial and unambiguous way, so that its effect is powerful enough to show up in asset prices. Second, it must be shown to impact the mood of a large proportion of the population, so that it is likely that enough investors are affected. Third, the effect must be correlated across the majority of individuals within a country.

We believe that results from international soccer competitions are a mood variable that satisfies these criteria. There is a multitude of psychological evidence that sports results in general have a significant effect on mood. Wann, Dolan, Mcgeorge, and Allison (1994) document that fans often experience strong positive reactions to watching their team perform well and a corresponding negative reaction when the team performs poorly. More importantly, such reactions extend to increased or decreased self-esteem and to positive or negative feelings about life in general. For example, Hirt, Erickson, Kennedy, and Zillmann (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 following a loss. Schwarz, Strack, Kommer, and Wagner (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 view on national issues. A related study by Schweitzer, Zillmann, Weaver, and Luttrell (1992) shows that students rooting for the winning team of a televised American football game assessed both the probability of a 1990 war in Iraq and the potential casualties as significantly lower than fans from the losing team. Changes in mood also affect economic behavior. Arkes, Herren, and Isen (1988) find that sales of Ohio State lottery tickets increased in the days after a victory by the Ohio State University football team. Since sports results have been shown to affect subjects' optimism or pessimism about not just their own abilities, but life in general, we have a strong reason to hypothesize that they impact investors' views on future stock prices.[3]

As a testament to the fundamental importance of sports, the effects of sports results extend far beyond simple mood changes. Sports results have in many cases been found to have such a strong effect that they adversely affect health. Carroll, Ebrahim, Tilling, Macleod, and Smith (2002) show that admissions for heart attacks increased by 25% during the three day period starting on June 30, 1998—the day England lost to Argentina on a World Cup penalty shootout.[4] White (1989) documents that elimination from the US National Football League playoffs leads to a significant increase in homicides in the relevant cities following the games. Wann, Melnick, Russell, and Pease (2001) list several cases of riots after disappointing sports results and cite a multitude of other papers on the same issue. Trovato (1998) finds that suicides among Canadians rise significantly if the Montreal Canadiens are eliminated early from the Stanley Cup

[3]For other related studies see Sloan (1979), Wann and Branscombe (1995), Platow, Durante, Williams, Garrett, Walshe, Cincotta, Lianos, and Barutchu (1999), and Bizman and Yinon (2002).

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

playoffs.

In addition to the psychological evidence showing that sporting events in general impact human behavior, there is ample evidence showing that soccer in particular is an important part of many people's lives. This explains the motivation for our primary choice of sport. 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. On average more than 20 million Italians watch their national team in the final stages of the World Cup or European Cup, while Spain and England's local audiences are well above 10 million.[5] Moreover, national soccer results influence the mood of the entire country in a similar way. Other popular sports, such as American football and baseball, are predominantly contested on 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.

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 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. The increase in heart attacks, crimes, and suicides that accompany sporting losses, with no evidence of improvements in mood of similar magnitude after wins, suggests that we should expect 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. Thus, the reference point against which gains and losses are measured becomes an important determinant of utility. The natural reference point in our setting is supporters' pre-game expectations of how their team will perform. A number of studies have shown that fans are subject to an "allegiance bias"—the rendering of biased predictions by individuals who are psychologically invested in a

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

[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 has been 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, Erickson, Kennedy, and Zillmann (1992).

desired outcome (see Markman and Hirt (2002); Wann, Melnick, Russell, and Pease (2001)). Thus, if the reference point of soccer fans is that their team will win, we may expect to 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 loser is immediately removed from the competition.

3 The data

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

International soccer competitions have used slightly different formats throughout the last thirty years. As of 2004, national teams from different geographic regions play against each other to qualify for the World 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." This stage starts with a round of sixteen, in which no ties are allowed. 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 9 for details). There are a total of 1,162 soccer matches, 638 wins and 524 losses, that we define as relevant "mood events." This includes all elimination and group games in the World Cup and the continental cups—a total of 756 games. In addition, we add another 406 relevant qualifying games. Owing to the large disparity in skill among participating countries in a typical qualifying group, a national team will usually play only 4-6 matches that will be critical for its qualification and thus will have a significant mood impact.[8] To select games that has a reasonable chance of being important, we use closeness in opponents' ability as a proxy for importance. Ability is measured using Elo ratings, obtained from `www.eloratings.net`. [9] A qualifying game is defined as close if the Elo rating of the two opponents are within 125 points (after adding 100 points to the team with home advantage) or

[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 a mood event.

[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.

if the game is played as part of the knock-out 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 country ranked 10th (Portugal) is 122 points.

The data on cricket, rugby, ice hockey, and basketball are collected from various web sources. The cricket matches are One Day Internationals played over the period 1975 to 2004. The rugby matches are 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 are the World Championships (1998 to 2004), the Olympics (1980 to 2002), and World Cup/Canada Cup (1996 and 2004). The basketball matches are the Olympics (1992 to 2004) and the 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 gives on average 388 games for each of these four sports. About 45% of the additional sample is comprised 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. Returns are computed 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.

4 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. For some weekday games, the market is open while the match is being played. Nevertheless, to ensure that we have the return for a full day when the game outcome is known, we choose to use the first trading day after the match for all games. If anything, this potential asynchrony attenuates our results since part of the reaction may have been incorporated in prices before our measurement day.

4.1 Descriptive statistics

Table 1 provides information about the number of games included in the sample for each sport as well as mean daily log returns on the stock markets on days following game days and on non-game days. For the sample of soccer countries in Panel A, there are 181,796 trading days that are not associated with a soccer match. The average return and standard deviation for these days is 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 1. 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: the cricket point estimates are 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, there are a total of 10 different and 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 positive with the exception of the rugby subsample, where the difference is negative, but by less than one basis point. Therefore, in nine of the ten subgroups the point estimates show a positive difference between win and loss days. The probability that there are nine or more successes out of ten equally likely Bernoulli trials is 1%. Thus, the null hypothesis of similar return after wins and losses can easily be rejected at conventional levels of statistical significance. In sum, even ignoring the actual size of the differences, the evidence in Table 1 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, the 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 there is at least one country that won and only 96 days for which at least one country lost. If there are common shocks to stock returns across different countries, return observations on event dates will not be independent. Moreover, for all the sports, many matches are played between Friday afternoon and Sunday afternoon. Thus, we measure the daily return on Monday for all these games. This may potentially introduce a spurious day-of-the-week relationship between soccer results and stock returns. The next section details the econometric approach we are following to deal with these and other issues that may influence our results.

4.2 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 that losses lead to a negative reaction. This is motivated by the findings from the psychology literature that wins are associated with good mood and losses with bad mood.

Under the null hypothesis, soccer outcomes are uncorrelated with asset prices. This in turn implies that the effects of soccer will 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:

$$R_{it} = \gamma_{0i} + \gamma_{1i}R_{it-1} + \gamma_{2i}R_{mt-1} + \gamma_{3i}R_{mt} + \gamma_{4i}R_{mt+1} + \gamma_{5i}D_t + \gamma_{6i}Q_t + \epsilon_{it}; \tag{1}$$

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 US dollar return on Datastream's world market index on day t, and $D_t = \{D_{1t}, D_{2t}, D_{3t}, D_{4t}\}$ 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 one through five 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 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-squared 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 following regression model:

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

where $W_{it} = \{W_{1it}, W_{2it}, \dots\}$ are dummy variables for wins in different game sub-groups and $L_{it} = \{L_{1it}, L_{2it}, \dots\}$ are loss-dummies for the same set of game sub-groups. The number of game sub-groups will vary depending on the setting. More specifically, W_{git} is a dummy variable that equals one if country i won a soccer match in game sub-group 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} is a dummy variable for losses defined analogously to the win dummy. As in

[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.

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, have shown that stock index returns have time-varying volatility. If international soccer competitions occurred during periods of high volatility, the magnitude of our coefficient estimates would be biased upward. To address this issue we model stock return volatility using a GARCH model as developed by Engle (1982) and generalized by Bollerslev (1986). Stock returns are model using equation (1). The volatility of the error term from this regression is modeled as a 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. The time series $\hat{\sigma}_{it}^2$ is used to form a 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, our analysis is done 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."

4.3 The loss effect

Table 2 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 days after a loss by the national soccer team. The 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 estimates for the loss effect are increasing in game importance. First, the World Cup games show a bigger loss effect than 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 soccer competitions should have the strongest mood effect. They 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 either 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 other 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 Panel Corrected Standard Errors. 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, fans' attention 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 2 reports the results using the abnormal normalized returns described in Section 4.2. 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 from 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 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 1), 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 is 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 not statistically distinguishable from zero.[11]

When comparing across competitions and stages in Panel A of Table 2, it appears that the loss effect is increasing in game importance. In Table 3 we further explore this issue by investigating whether the effect is stronger in countries where soccer is of greatest importance. We split the sample into "Top Seven soccer nations" and "Other soccer nations." The Top

[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 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.

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 3 contains the results for the Top Seven countries while Panel B contains results for 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 2 is not purely driven 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]

4.4 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 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 inadequately captured by the Datastream world index, which is mostly composed of returns from developed nations. To mitigate the problems created by the 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 4 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 2, aside from a small fall 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

[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.

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 is motivated by Pinegar (2002), who shows that the clock change results of Kamstra, Kramer, and Levi (2000) are sensitive to outliers in their data. We define outliers as observations where 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. This approach effectively identifies the observations that have the greatest influence on the estimates of β_W and β_L.

Panel B in Table 4 reports trimmed means where 20% of the game-day observations is 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), in particular chapter 3). Again, we find that the loss effect documented in Table 2 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 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.

4.5 Evidence from other sports

Panel B of Table 2 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 2, it is clear that the loss effect is strongest in the sub-samples 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 look at 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 have defined as soccer nations, we expect that other sports will exhibit a weaker effect. A possible exception would 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, about 75% of sports related advertising revenues in India is generated through cricket events. 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 5 reproduces the analysis in Tables 2 and 4 for our sample of other sports. Somewhat surprisingly, given the lesser importance of these sports, Panel A of Table 5 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. The effect is negative for all subsamples but ice hockey, and 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 2 (consistent with the other sports being a weaker mood variable), the data supports the hypothesis that these other sporting events are also associated with stock market movements.

The last two panels of Table 5 perform robustness checks along the lines of those in Section 4.4. 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 strong statistical significance using either portfolio returns or trimmed means, partly as 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 out 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 2 through 5 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.

5 Soccer, mood, and economics

Our study was 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 on TV,

[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.

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 put the results in perspective, 40 basis points of the UK 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 particularly held by local investors and 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.

5.1 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, 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 if country i won a soccer match on a day that makes t the first post-game trading day and zero if the game was lost, and v_{it} is an 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 discussed in section 2, the allegiance bias suggests that agents' beliefs may not be closely related to expectations computed under objective probabilities—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 were the world's top ranked team and eventually won the competition. This contrasts with the 42% probability that bookmakers assigned to a victory. Second, even if we had data on subjective probabilities, 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 indeed less painful as they are less unexpected. At the same time, 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 obtained 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 outcome.

The estimation of equation (4) is conducted in two stages. First, we estimate $\tilde{\epsilon}_{it}$ as described in section 4.2. 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 6 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

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

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

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 would win the match. Focusing first on the sample of all games, the intercept is negative, close to the point estimate for losses from Table 2, and 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 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 6 reports results from the estimation of the model in equation (4) under the restricted parameters. Since the model implies both equality restrictions and inequality restrictions, it is estimated using quadratic programming. In particular, we estimate the model under the parameter restrictions above and 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 6 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 for why 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 where investors are rational, which implies that $E(W_{it})$ should be identical to p_{it}. 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 big soccer nations are overrepresented in our sample, the average p_{it} is 0.62. One immediate implication 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 2, which shows that the loss effect is 13 times as large as the win effect.

5.2 Portfolio characteristics and local ownership

If it is the mood of local investors that drives our results, we would expect stocks with an especially high local ownership to be more sensitive to soccer results. The models of Merton (1987) and Gehrig (1993) predict that foreigners will underweight stocks where their informational disadvantages are greatest. It seems reasonable to believe that small stocks with low analyst and media coverage (Bhushan (1989)) and growth firms where "hard" accounting information is a less important driver of firm value, would characterize firms where foreigners are at an informational disadvantage. This prediction is supported by 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 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 (2005) find that small stocks are more strongly affected by investor sentiment. Hence, both differences in the extent of local ownership and the effect of sentiment given a particular ownership structure lead to a cross-sectional prediction that soccer results will 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 7 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 by foreigners having equal access to the individual firms that constitute the value/growth indices.

5.3 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 a model of variance: $\log(\hat{u}_{it}^2) = \gamma_{1i} y_{it} + \epsilon_{it}$, where y_{it} is a second set of explanatory variables. Finally, 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 does not start until the beginning of the 1980s, which reduces the number of soccer matches that can be included in the sample. Table 8 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 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 drop in volume on the loss days. It seems justified to 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 sad 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 also it has the potential of generating profits to negate the negative mood.

6 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 exceeds 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 the 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 rational investors' reaction to cash flow relevant information. Instead, we interpret the effect as resulting from the impact of sports results on

[16] Compared to the 39 countries in Table 9, the missing countries are Bahrain, Croatia, Jordan, Nigeria, and Saudi Arabia.

investor mood. There are several justifications for this interpretation. First, soccer results were chosen as an event precisely because they are believed to impact mood and 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 previously been found to be especially affected by investor sentiment, and they 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 would have obtained large excess returns by trading on these mood events. One such strategy would be to short futures on both countries' indices before an important match to exploit the asymmetry of the effect. However, the events we cover do not seem to occur with enough frequency to have a portfolio fully dedicated to trading on them. Moreover, the effect seems to be particularly strong in small stocks and involves shorting, which suggests that even traders facing 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, but to document that mood can have a large effect on stock returns—significantly expanding 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 was reasonably liquid at the time of the starting date. The starting date is the first date for which the five-day average number of firms in the index is at least 10 and the average number of firms (over a five 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 on the value one before these dates and is zero otherwise. None of our reported results are influenced by the trimming or the inclusion of the time dummies. The second column of Table 9 reports the starting date for the returns time series.

For the analysis in Table 7 we use data on large indices for 18 countries out of the 39 soccer countries listed in Table 9. 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 available from Datastream for 34 out of the 39 soccer countries listed in Table 9. 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 where the price of fewer than three of the stocks in the index moved and there was no trading volume. We identify more than 95% of the holidays this way. The remaining holidays are identified using the same two criteria separately.

Volume data is available for all countries for which Datastream provides a TOTMK index. For some countries, the volume data contains multiple zero-volume days at the beginning of the time series. To reduce the overall volatility of the volume time series for country i, we set the start date of the time series as the first date where volume has exceeded 100 for five consecutive days.

B Soccer

We collect international soccer results from the website `www.rdasilva.demon.co.uk` for the period January 1973 through December 2004. The data were checked for errors manually 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 where we have return data) in either the World Cup or the continental cups. These sampling 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 USA, these countries are excluded. Table 9 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 twelve teams proceeded to the second round and the four top teams played in the semi-finals. For this year also we have defined the second round games as elimination games.

C Cricket

Cricket has traditionally been 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 unclear 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. The cricket results are obtained from the website of the ICC: `www.icc-cricket.com`. We define as cricket nations those that were ranked in the top ten countries every year between 2002 and 2005 (the top ten did not change over this period). When we restrict the countries to 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 9 reports the number of cricket wins and losses.

D Rugby

International rugby data were obtained from the website `www.rugbyinternational.net`. Data for Australia from 2001 and South Africa were unavailable from the website owing to a broken link and were obtained directly from the website 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 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 9 reports the number of rugby wins and losses.

E Ice hockey

Ice Hockey data is collected from the website `www.iihf.com` of the International Ice Hockey Federation (IIHF) and the independent website `www.hockeynut.com`. The hockey matches are the World Championships (1998 to 2004), the Olympics (1980 to 2002), and World Cup/Canada Cup (1996 and 2004). We define ice hockey nations as the top ten countries based on performance in the 2004, 2003, 2002, and 2001 World Cup and the 2002 Olympics. As for soccer, the USA 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 9 reports the number of ice hockey wins and losses.

F Basketball

World Championship and Olympic basketball results were obtained from `www.fiba.com`. The website contained, for each tournament, the names of the two opponents, the round and the result. Unfortunately it did not contain dates, so these had to be obtained from a variety of other sources. Olympic dates were obtained from `sports.espn.go.com/oly/index` for 2004 and

2000, and `www.sunmedia.ca/OlympicsBasketball/sked.html` for 1996. World Championship dates were 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 USA's dates were 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 a country to have 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 there are at least two other sports (cricket and rugby) that are more important in terms of attention in these countries. Again, we remove the USA 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 US. The removal leaves us with eleven basketball nations: Argentina, Brazil, Canada, China, France, Germany, Greece, Italy, Lithuania, Russia, and Spain. Table 9 shows reports the number of basketball wins and losses for these eleven 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 one 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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Table 1
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), the Olympics (1980 to 2002), and World Cup/Canada Cup (1996 and 2004). The basketball matches are the Olympics (1992 to 2004) and the World Championships (1994 to 2002). 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 where the loser is eliminated from further play in the tournament. Group games are played during the championship and qualifies 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	Std.	N	Mean	Std.	N	Mean	Std.
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
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

Table 2
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 between countries, W_{it} is a dummy variable that takes on the value one if country i won a soccer match on a day that makes t the first trading day after the match and is 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 in date t in country i, R_{mt} is the continuously compounded daily US 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, $Q_t = \{Q_{1t}, Q_{2t}, Q_{3t}, Q_{4t}, Q_{5t}\}$ are dummy variables for days for which the previous one through five days are non-weekend holidays. Panel B reports the estimates for β_W and β_L when the "abnormal normalized returns" defined in section 4.2 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 Table 1 and the appendix for sample details.

	Wins			Losses		
	Num. games	β_W	t-val	Num. games	β_L	t-val
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
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

Table 3
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 4.2 and described in Table 2. W_{it} is a dummy variable that takes on the value one if country i won a sports match on a day that makes t the first trading day after the match and is 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 stage, and European Championship qualifying stage. 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.)

	Wins			Losses		
	Num. games	β_W	t-val	Num. games	β_L	t-val
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
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

Table 4
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 4.2 and described in Table 2. 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 statistic reported is obtained by using as an estimate of the standard error of the mean estimate $\mathrm{SD}(\tilde{\epsilon}_{jt})/\sqrt{N-1}$. Panel B reports 10%-trimmed means of the residuals $\tilde{\epsilon}_{it}$. Observations where 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 where W_{it} equals one are removed in a similar way. Compared to Table 2 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-val	N	β_L	t-val
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
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

Table 5
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 4.2. W_{it} is a dummy variable that takes on the value one if country i won a sports match on a day that makes t the first trading day after the match and is 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-statistic t-val 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). Panels B and C replicate the analysis in Table 4 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-val	N	β_L	t-val
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
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
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

Table 6
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:

$$\epsilon_{it} = \alpha_0 + \alpha_1 W_{it} + \alpha_2 p_{it} + v_{it};$$

where ϵ_{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 won a soccer match on a day that makes t the first trading day after the match and zero if a game was 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 5.1. Elimination matches are matches where 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.

	Num. games	α_0 (t-value)	α_1 (t-value)	α_2 (t-value)	Wald-D (p-value)
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)	
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)

Table 7
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 on the value one if country i won a soccer match on a day that makes t the first trading day after the match and is zero otherwise, and L_{it} is a dummy variable for losses defined analogously. $\tilde{\epsilon}_{it}$ are the "abnormal normalized returns" defined in section 4.2 and described in Table 2, 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 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 9.

	Wins			Losses		
	Num. games	β_W	t-val	Num. games	β_L	t-val
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

Table 8
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 a model of variance: $\log(\hat{u}_{it}^2) = \gamma_{1i} y_{it} + \epsilon_{it}$, 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 where 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 9, the missing countries are Bahrain, Croatia, Jordan, Nigeria, and Saudi Arabia. For most countries Datastream volume data does not start until the beginning of the 1980s. The t-statistic is computed by allowing the variance of u_{it} to be country specific, and u_{jt} and u_{it} to be contemporaneously correlated.

	Wins			Losses		
	Num. games	β_W	t-val	Num. games	β_L	t-val
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

Table 9
Mean daily percent national index return and number of wins and losses in international team sport matches

			Soccer		Cricket		Rugby		Ice hockey		Basketball	
Country	Time series begins	Mean log return	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