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A meta-regression analysis

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Jerome Geyer-Klingeberg[1], Markus Hang[1], Matthias Walter, Andreas Rathgeber[1]

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[1] Institute of Materials Resource Management, University of Augsburg

University of Augsburg, D-86135 Augsburg
Visitors: Universitätsstr. 12, 86159 Augsburg
Phone: +49 821 598-4801 (Fax: -4899)

University of Bayreuth, D-95440 Bayreuth
Visitors: Wittelsbacherring 10, 95444 Bayreuth
Phone: +49 921 55-4710 (Fax: -844710)

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Do stock markets react to soccer games? A meta-regression analysis

Jerome Geyer-Klingeberg [a], Markus Hang[a], Matthias Walter[b] and Andreas Rathgeber[a]

[a]Institute of Materials Resource Management, University of Augsburg, Augsburg, Germany; [b]FIM Research Center, University of Augsburg, Augsburg, Germany

ABSTRACT
This study applies meta-regression analysis to aggregate a sample of 1126 empirical estimates of the stock market reaction to soccer matches collected from 37 primary studies. Our results indicate that winning a match is not associated with significant return effects for both national teams and individual clubs. In the case of lost matches, we find strong evidence for publication bias, i.e. negative returns are systematically overrepresented causing a biased picture of the true soccer match effect. After correcting for this bias, the mean return after losses by national teams becomes statistically insignificant and accounts for only − 5 basis points. In the case of individual clubs, the corrected impact of a loss is a significant − 39 basis points effect. In a further analysis, we identify various aspects of study design like regional differences, time period under examination and the design of empirical analysis to be responsible for the wide variation in previous study outcomes. Overall, our findings provide evidence against the hypothesis that stock markets are driven by sports sentiment in the case of national teams. Due to the existence of strong asymmetry in the returns after wins and losses of individual clubs, behavioural explanations cannot be fully ruled out.

KEYWORDS
sports sentiment; soccer; stock returns; meta-analysis; publication bias

JEL CLASSIFICATION
C83; G14; L83

I. Introduction

According to the efficient market hypothesis, an asset market is considered to be information-efficient if prices reflect all available information relevant for their future value (Fama 1970). In sharp contrast to traditional finance theory, numerous studies have challenged the rationality of financial markets by documenting non-rational components in asset pricing and behavioural biases in investors' decision-making (among others, Chang et al. 2008; Hirshleifer and Shumway 2003; Saunders 1993). A major strand of the literature in this area examines the impact of sports results on financial markets (among others, Brown and Hartzell 2001; Chang et al. 2012; Edmans, Garcia, and Norli 2007; Kaplanski and Levy 2010). Especially the effect of soccer matches on stock returns has received broad attention in recent research (among others, Ashton, Gerrard, and Hudson 2011; Edmans, Garcia, and Norli 2007; Ehrmann and Jansen 2016; Scholtens and Peenstra 2009).

The findings of the existing research record on the relation between soccer matches and stock returns are rather inconclusive. For the impact of national soccer teams' results, some studies report a statistically significant relationship (among others, Ashton, Gerrard, and Hudson 2011; Edmans, Garcia, and Norli 2007; Kang and Park 2015). In contrast, other authors find no evidence for a financial impact of national soccer match outcomes on financial markets (among others, Gallagher and O'Sullivan 2011; Klein, Zwergel, and Heiden 2009; Vieira 2012). For the influence of publicly traded soccer clubs, the picture is less ambiguous, as many studies report at least partially significant influence of soccer matches on the clubs' stock prices (among others, Castellani, Pattitoni, and Patuelli 2015; Dobson and Goddard 2001; Renneboog and Vanbrabant 2000). Nevertheless, the actual size of the return effect after matches of individual clubs strongly differs across previous literature.

Given the disagreement on the existence and magnitude of the soccer match effect, academics have sought explanations for the large diversity in reported results. Klein, Zwergel and Fock (2009) conduct a replication study of the seminal contribution by Ashton, Gerrad and Hudson (2003)[1] and

CONTACT Jerome Geyer-Klingeberg jerome.geyer-klingeberg@mrm.uni-augsburg.de; Andreas Rathgeber andreas.rathgeber@mrm.uni-augsburg.de

[1]Ashton, Gerrad and Hudson (2003) find a strong association between the performance of the English national soccer team and daily changes in the FTSE 100 index.

demonstrate that after correcting minor errors in the data preparation as well as changing the observation period, the initially significant findings turn out to be insignificant. As a consequence, Klein, Zwergel and Fock (2009) hypothesize that the inconclusive evidence on the soccer match effect of national teams might be driven by a kind of publication bias, i.e. the favour of authors, editors and reviewers to publish results that are statistically significant and consistent with theoretical predictions.[2] If authors prefer specific results and thus change their model setting or data sets until they find the desired outcomes (e.g. a significant and negative return effect after lost soccer matches), specific estimates will be systematically underrepresented in the literature (e.g. insignificant or positive returns after losses). If results are selectively reported, inferences made from the existing research record will be distorted, leading to an incorrect overall picture of the true soccer match effect. Many previous meta-studies in other fields of economics emphasize that the issue of publication bias is a serious threat for the integrity of the empirical research process (among many others, Doucouliagos and Stanley 2009; Feld and Heckemeyer 2011; Görg and Strobel 2001).

Based on the mixed empirical findings as well as the potential problem of publication bias, our study offers three main contributions. First, we use meta-regression analysis (hereafter MRA) to provide the first quantitative review of studies investigating the stock market behaviour after soccer matches. Second, we statistically test for the presence and magnitude of publication bias. This approach allows a quantitative investigation of the publication bias hypothesis discussed by Klein, Zwergel and Fock (2009) and extends it also to soccer matches of individual clubs. Third, we use a multiple MRA approach to statistically explore which aspects of study design are responsible for the wide heterogeneity in existing empirical findings. Through this analysis, MRA enables us to provide several new insights into the relation between soccer match results and stock returns.

The remainder of the article is structured as follows. Section II shortly reviews the theoretical background and explains how the soccer match effect is estimated. Section III outlines the data collection and data preparation. Section IV presents the MRA methodology and describes the sources of heterogeneity. Section V reports and discusses the empirical results. Lastly, Section VI concludes.

II. Estimating the effect of soccer games on stock returns

There are two strands of theories linking soccer match results with stock market returns. Neoclassical finance argues that investor reactions are purely fundamental and originate from a revaluation of match-related economic consequences (efficient market hypothesis) (Fama 1970). For example, winning a soccer match induces direct and indirect cash flow effects through increasing revenues from merchandize sales, broadcasting contracts, gate attendances or prize money (and vice versa for losses). Opposed to the rationality paradigm, behavioural finance theory proposes that investors are subject to behaviourally driven effects (Shiller 1984), which, among others, arise from mood changes after sports games (sports sentiment hypothesis). In other words, asset pricing is the result of a process that also accounts for psychological elements, such as a feel-good factor or overconfidence about the future induced by the match outcome (Kerr et al. 2005; Schwarz et al. 1987; Wann et al. 1994).

To empirically quantify the stock return effect of soccer games, previous literature mostly applies event study methods. The general approach is a two-stage regression-based event study model as proposed in the seminal contribution by Edmans, Garcia and Norli (2007). The first stage represents a market model including additional variables for confounding effects.[3] The second stage quantifies the impact of the soccer match outcomes on the abnormal returns derived from the first stage regression:

$$\hat{\varepsilon}_{it} = \beta_0 + \beta_W W_{it} + \beta_L L_{it} + u_{it}, \tag{1}$$

[2]It should be noted that we use the term 'publication bias' to refer to selective reporting independent of a study's publication status. As unpublished work like manuscripts and conference papers are written with the aim to get published, there is no reason to assume that the risk of selective reporting is lower in unpublished studies.

[3]For example, lagged returns to control for first-order serial correlation, controls for day-of-the-week effects, or controls for non-weekend holidays.

where i denotes a specific national team or individual soccer club, t is a time index for each trading day, $\hat{\varepsilon}_{it}$ denotes the residuals from the first stage regression, W_{it} is a dummy variable equal to one on the first trading day after a team won a match and L_{it} is a dummy equal to one on the first trading day after a team lost a match. For trading days without matches on the previous day or for drawn matches,[4] both variables are equal to zero.

For the meta-analysis performed in this study, we manually collect the estimates of the coefficients $\hat{\beta}_W$ and $\hat{\beta}_L$ from the primary studies, as they capture the abnormal returns associated with the match outcomes. Since the coefficients represent stock returns, the effects are directly comparable across studies and thus allow aggregation.

III. Data and sample construction

Literature search

For the identification of the meta data set, a four-step search procedure was applied.[5] (1) We searched major scientific databases (ABI/Inform Complete, Academic/Business Source Premier, EconLit, Google Scholar, SSRN) for relevant empirical studies on the relation between soccer match outcomes and stock returns.[6] (2) We performed a backward search in the reference lists of the articles identified during the database search. (3) We used the 'cited by'-option in Google Scholar to screen all references citing articles identified in the database search. (4) We manually screened the publication lists of all authors with relevant studies available in the electronic databases.

During the literature search, only studies that meet the following selection criteria are retained in the sample[7]:

- Studies must report return estimates for the stock market response to wins or losses of national teams or individual clubs.
- Articles reporting estimates that cannot be clearly assigned to a win or loss are excluded from the sample. This is necessary as different match results are likely to be followed by different return reactions. Pooling estimates for wins and losses in one single measure would blur these effects.
- A measure of precision of the estimate for the stock market reaction must be reported (i.e. either SEs, t-statistics or p-values). The information about precision is obligatory to identify and control for publication bias in the MRA model.

Applying the selection criteria on the set of articles identified during the literature search produces a final sample of 37 primary studies. Within this sample, 30 articles are published in academic journals. The other seven studies are contributions from academic conferences, working papers and book chapters.

Data preparation

From all 37 studies, we extract the estimates $\hat{\beta}_W$ and $\hat{\beta}_L$ (see Equation 1). To ensure comparability, we transform the return estimates into percentage values. Normalized abnormal returns are multiplied by the standard deviation of the particular time series to obtain the non-standardized abnormal returns.

As most authors routinely report more than one estimate (e.g. results from different model specifications, subsamples or robustness checks), we follow an established standard in MRA research and include all estimates in order to maximize the information available (among others, Feld, Heckemeyer, and Overesch 2013; Hang et al., 2017; Havranek et al. 2015).[8]

The majority of estimates measure the return reactions on the first trading day after the games (76%). As previous literature finds evidence that financial markets might generate a lagged return

[4]In contrast to wins and losses, it is unclear how draws impact rational decisions or investor sentiment. Thus, we follow previous primary studies and do not analyse the return reactions after drawn matches (among others, Edmans, Garcia, and Norli, 2007; Kang and Park, 2015).
[5]For the literature search and the subsequent meta-analysis, we follow best practices for MRA research issued by the Meta-Analysis for Economics Research network (Stanley et al., 2013).
[6]Our search command consists of a combination of keywords related to soccer (soccer, football, sporting result, sport sentiment) and stock returns (stock return, stock price, economic impact).
[7]The complete list of excluded studies is available on request from the authors.
[8]Picking only one or a few estimates from each study (e.g. the 'best-set' or the 'average-set' of estimates) causes additional biases, requires objective selection rules to decide which estimate to prefer and leads to a loss of information about within-study variation (Stanley and Doucouliagos, 2012).

reaction, especially to bad news (Chan, 2003; Palomino, Renneboog, and Zhang, 2009), we also include returns measuring lagged effects.[9] In the full sample, 24% of the estimates refer to more than 1 day after the match.

Finally, our sample consists of 1126 estimates for the return reaction after soccer matches, where 548 refer to won matches and 578 to losses. Altogether, the sample provides evidence from a total of 29,066 soccer matches across 60 countries and 56 soccer clubs. Table 1 provides a detailed overview of the articles and the extracted estimates. In the full sample, the mean stock return after wins is 0.38%; after losses, the effect is about twice as large (−0.76%). The overview also shows that the number of significant findings is 162 out of 548 estimates for wins, and 244 out of 578 estimates for losses, which provides a first indication for an asymmetry effect in the stock market response.

IV. Empirical models

> *Because publication selection is caused by the process of conducting empirical economic research itself, conventional econometrics is incapable of correcting or estimating this effect. Hence, some 'macro' perspective is required that looks across an entire research field, and this is precisely what MRA provides.*
>
> (Stanley and Doucouliagos 2012, 4)

MRA is a statistical tool to systematically review previous empirical results on the same economic effect (Stanley, 2001). Its main advantage against a primary study is that it minimizes random estimation error by averaging across the entire research record, allows to detect and correct for publication bias and identifies variables explaining the variability in existing research results (heterogeneity). MRA has become the most frequently used technique for research synthesis in many areas of economics research (among others, Card, Kluve, and Weber, 2010; Geyer-Klingeberg et al., 2017; Havranek and Irsova, 2011; Minviel and Latruffe, 2017; Velickovski and Pugh, 2011).

Publication bias

If researchers share a preference for reporting certain study outcomes (e.g. a significant negative return effect after losses of national teams) and therefore discard results from publication if they do not comply with their preference ('file drawer problem'), literature as a whole exaggerates the effect in question. Previous studies reveal that publication bias is present in many areas of economics (among others, Doucouliagos, Stanley, and Viscusi, 2014; Havranek et al. 2015; Møen and Thorsen, 2017). For example, in financial economics, Harvey, Liu and Zhu (2016) and Harvey (2017) recently outlined the presence of strong selective reporting of significant research results in factor studies explaining the cross-section of expected returns.

For a first visual investigation of publication bias, we examine the distribution of collected estimates via funnel plots.[10] Funnel plots show the observed soccer match effects and their precision, which is the inverse of the estimates' SEs, in a scatter diagram (Stanley and Doucouliagos, 2010). In the absence of selective reporting, the plot should resemble a symmetrical inverted funnel, where the most precise estimates (those with the smallest SEs) are concentrated close to the top and estimates with larger confidence intervals are more widely dispersed at the bottom of the graph. In other words, even if the true effect would be negative, we should observe also positive estimates with large SEs (due to the law of chance). If specific estimates (e.g. positive effects after losses) are systematically omitted from publication, the funnel plot exhibits asymmetry.

For a statistical analysis of funnel plot asymmetry and thus publication bias, we follow previous literature (among others, Ashenfelter, Harmon, and Oosterbeek, 1999; Doucouliagos, Stanley, and Giles, 2012; Havranek, 2015) and analyse the relation between the observed estimates and their SEs. This test is based on the idea that, in the absence of publication bias, the effect estimates and their SEs should be statistically independent quantities. However, if researchers prefer statistically significant results, they will search for large return effects to offset SEs and to yield an adequate

[9]Due to confounding events, lagged return effects are difficult to measure for the impact of national teams' results on broad stock indices. Therefore, lagged effects are only available in studies examining individual soccer clubs.

[10]We use funnel plots only for a first visual indication about selective reporting. Inferences about publication bias are drawn from statistical testing of publication bias.

level of statistical significance. Such preference for specific results leads to a correlation between the effect estimates and their SEs, which can be tested by the following model (Card and Krueger, 1995):

$$b_{ij} = \beta_0 + \beta_1 SE_{ij} + \varepsilon_{ij}, \qquad (2)$$

where the dependent variable b_{ij} is the ith observed estimate of the stock return effect from study j, SE_{ij} are the reported SEs of the estimates and ε_{ij} is the error term. The slope coefficient β_1 measures asymmetry in the funnel plot and thus publication bias (Egger et al., 1997). The intercept β_0 denotes the mean return effect on the condition that SEs approach zero. Thus, the intercept value can be interpreted as the underlying effect corrected for publication bias (Stanley, 2005).

Heterogeneity

The MRA model in Equation (2) assumes that differences across studies arise from random sampling error and publication bias. However, estimates are obtained from studies that use different data sets and methodological approaches. This leads to systematic differences (heterogeneity) among the estimates. To account for this variation, we add a set of moderator variables, which are suspected to systematically affect the heterogeneity in reported results:

$$b_{ij} = \beta_0 + \beta_1 SE_{ij} + \sum_{k=1}^{K} \gamma_k Z_{ijk} + \eta_{ij}, \qquad (3)$$

where Z_{ijk} are moderator variables capturing differences in study design. It should be noted that the intercept (β_0) still denotes the underlying soccer match effect corrected for publication bias but now must be interpreted together with the Z variables. In the specification above, the intercept represents the soccer match effect conditional on $\mathbf{Z} = 0$.

MRA model specification

There are some caveats to consider during estimation of Equations (2) and (3). First, the variance of the estimates b_{ij} fundamentally depends on a study's sample size, which is indeed largely different across studies (see Table 1). The common way to address this heteroscedasticity is to apply weighted least squares (WLS) regression with the inverse of the estimates' variance as weights. Stanley and Doucouliagos (2017) recently exposed in a simulation study that the WLS approach outperforms other MRA methods. This inverse-variance weighting implies that more precise estimates, which are typically observed from studies with large sample sizes, are given a greater weight and thus more influence on the mean effect (precision weighting). A second issue occurs, since the inclusion of multiple estimates per study introduces within-study dependencies. We account for non-independent estimates by clustering the SEs at the level of each study.

As baseline model, we employ a WLS regression with SEs clustered at the study-level. This is the most established and frequently used method in MRA research (among others, Abdullah, Doucouliagos, and Manning, 2015; Laroche, 2016; Nelson and Kennedy, 2009). As robustness test, we follow Stanley and Doucouliagos (2012) and apply panel regression methods. We report the results from a WLS model with study-level fixed effects (FE) to control for unobservable study characteristics.[11] In addition, we apply a mixed effects model (ME) with study-level random effects estimated by maximum likelihood methods. For the three MRA model specifications (WLS, FE, ME), all estimations are conducted by inverse-variance weighting. A disadvantage of this approach is that it indirectly puts larger weights on studies that report more estimates. To avoid unintentional weighting of articles reporting multiple estimates, we follow recent MRA research (Havranek and Irsova, 2017; Zigraiova and Havranek, 2016) and add a fourth model with alternative weights, which account for the number of estimates extracted from each study. For the new weights, we use the inverse of the number of estimates reported per study and multiply it with the inverse of the estimates' variance. Accordingly, the new weights assign equal weights to studies independently of the number of reported estimates and simultaneously put more emphasize on more precise estimates within the same study.

Selection of moderator variables

In this section, we describe the moderator variables Z_{ijk} from Equation (3), which control for various sources of heterogeneity. All variables are manually

[11]We do not apply the fixed effects on Equation (3), because some of the moderator variables Z_{ijk} are constant within studies and thus would be perfectly correlated with individual study dummies in the fixed effects model.

Table 1. The meta data set.

Author(s)	Object of study	Sample period	Countries	No. of matches	Panel A: Wins Total no. of effects [significant effects]	Panel A: Wins Mean return (%)	Panel A: Wins SD (%)	Panel B: Losses Total no. of effects [significant effects]	Panel B: Losses Mean return (%)	Panel B: Losses SD (%)
Allouche and Sebastien (2008)	Clubs	1998–2001	England	681	26 [15]	0.55	0.84	21 [16]	−0.70	0.80
Ashton, Gerrard and Hudson (2011)	National teams	1984–2009	England	290	24 [3]	0.05	0.21	24 [1]	−0.29	0.19
Benkraiem, Louhichi and Marques (2009)	Clubs	2006–2007	6 Countries (Europe)	745	12 [3]	0.08	0.62	12 [3]	−0.48	0.95
Berkowitz and Depken (2017)	Clubs	1992–2008	England	951	3 [2]	0.42	0.21	6 [6]	−1.58	0.79
Bernile and Lyandres (2011)	Clubs	2000–2006	8 Countries (Europe)	626	13 [9]	1.31	1.28	17 [8]	−0.72	0.99
Berument and Ceylan (2012)	Clubs	1977–2007	4 Countries (global)	1543	2 [2]	0.80	0.70	2 [2]	−0.33	0.28
Berument, Ceylan and Onar (2013)	Clubs	1987–2011	Turkey	385	3 [1]	0.65	0.07	3 [3]	−1.39	0.05
Botha and Carl (2011)	National teams	1990–2010	South Africa	249	2 [0]	0.01	0.02	0 [0]	–	–
Castellani, Pattitoni and Patuelli (2015)	Clubs	2007–2009	10 Countries (Europe)	2157	25 [13]	0.63	0.87	25 [17]	−1.22	0.81
Demir and Danis (2011)	Clubs	2002–2009	Turkey	915	27 [1]	0.06	0.59	27 [22]	−1.62	0.60
Demir and Rigoni (2017)	Clubs	2003–2010	Italy	114	3 [3]	1.56	0.12	3 [2]	−0.83	0.02
Demirhan (2013)	National teams	1988–2011	Turkey	239	1 [0]	−0.10	0.00	1 [0]	−0.50	0.00
Dimic et al. (2017)	Clubs	2000–2013	6 Countries (Europe)	4347	42 [33]	0.78	0.71	42 [41]	−1.42	0.35
Dobson and Goddard (2001)	Clubs	1997–1999	England	164	8 [4]	10.23	13.78	26 [11]	−3.96	7.06
Duque and Ferreira (2005)	Clubs	1998–2002	Portugal	340	1 [1]	1.47	0.00	1 [1]	−1.00	0.00
Edmans, Garcia and Norli (2007)	National teams	1973–2004	39 Countries (global)	1162	36 [2]	−0.01	0.07	40 [24]	−0.18	0.10
Floros (2014)	Clubs	2006–2011	3 Countries (Europe)	179	4 [0]	−0.07	0.25	4 [1]	−0.48	1.25
Fotaki, Markellos and Mania (2009)	Clubs	1997–2004	2 Countries (Europe)	4793	1 [1]	0.23	0.00	1 [1]	−0.22	0.00
Fung et al. (2015)	Clubs	1999–2011	Turkey	278	90 [14]	−0.13	0.73	90 [11]	0.08	0.73
Gallagher and O'Sullivan (2011)	National teams	1989–2012	Ireland	95	12 [2]	0.07	0.32	13 [2]	−0.30	0.28
Gerlach (2011)	National teams	1974–2002	32 Countries (global)	328	0 [0]	–	–	3 [3]	−0.39	0.02
Jørgensen, Moritzen and Stadtmann (2012)	Clubs	2009–2011	Denmark	121	3 [0]	0.02	0.01	0 [0]	–	–
Kang and Park (2015)	National teams	1983–2012	Korea	166	6 [1]	0.17	0.25	6 [5]	−0.58	0.29
Klein, Zwergel and Heiden (2009)	National teams	1990–2006	13 Countries (Europe)	295	18 [2]	0.40	1.01	22 [0]	−0.06	0.28
Kolaric, Pusic and Schiereck (2015)	National teams	1998–2012	41 Countries (global)	1466	46 [2]	−0.06	0.18	46 [6]	−0.15	0.18
Majewski (2014)	Clubs	2001–2014	Italy	481	0 [0]	–	–	1 [1]	−1.09	0.00
Majewski and Majewska (2014)	Clubs	2004–2014	Germany	1337	3 [3]	−0.60	1.10	0 [0]	–	–
Morrow (1999)	Clubs	1996–1997	England	26	1 [0]	1.02	0.00	2 [1]	−2.14	1.16
Nicolau (2011)	Clubs	2000–2006	Spain	215	1 [1]	0.07	0.00	1 [1]	−0.19	0.00
Nicolau (2012)	National team	2010–2010	Spain	7	3 [3]	0.54	0.40	2 [2]	−0.87	0.99
Palomino, Renneboog and Zhang (2009)	Clubs	1999–2002	2 Countries (Europe)	916	32 [13]	0.80	0.73	32 [16]	−1.00	0.68
Renneboog and Vanbrabant (2000)	Clubs	1995–1998	2 Countries (Europe)	840	38 [10]	0.62	1.23	40 [14]	−0.82	1.57
Scholtens and Peenstra (2009)	Clubs	2000–2004	5 Countries (Europe)	1274	7 [4]	0.39	0.39	7 [7]	−1.69	0.75
Stadtmann (2006)	Clubs	2000–2004	Germany	174	5 [1]	1.67	0.92	8 [2]	−1.89	1.12
Vieira (2012)	National teams	2008–2010	31 Countries (global)	64	18 [4]	−0.09	0.70	18 [3]	−0.64	0.67
Vieira (2013)	National teams	2007–2008	14 Countries (Europe)	31	30 [9]	−0.43	0.62	30 [11]	−0.61	0.66
Zuber et al. (2005)	Clubs	1997–2000	England	1072	2 [0]	−0.14	0.01	2 [0]	0.31	0.02
Overall					**548 [162]**	**0.38**	**2.13**	**578 [244]**	**−0.76**	**1.85**

The table reports an overview of the 37 studies included in the meta-analysis sample. *Object of study* denotes if the study examines the soccer match impact of national teams or individual clubs. *Sample period* refers to the observation period of the data set (e.g. if the study examines games of the FIFA World Cup 2014, but the estimation of the expected return starts 250 days prior to the cup, the sample period is 2013–2014). *Countries* denotes the countries for which soccer matches are analysed in the primary studies' samples. *Matches* represents the total number of soccer matches in each study. The columns (6)–(11) contain the summary statistics for the effects extracted from the primary studies. *Total no. of effects* denotes the number of estimates extracted from each study. The number of effects that is found to be statistically significant, at least at the 5% level, is reported in brackets. *Mean return (%)* and *SD (%)* refer to the study-specific mean and SD of the reported stock return effects (both in percentage values). Missing information was requested from the study authors.

coded from the primary studies. In Table 2, the selected moderator variables are listed with their definitions, sample means and standard deviations.

Nationals teams versus individual clubs

An important difference in the design of primary studies concerns the dependent variable in Equation (1). The return variable in studies on national teams is commonly a broad national stock market index. In contrast, for publicly traded individual clubs, authors examine either return reactions of the club's stock price or a broad stock market index. The choice of the return variable affects the interpretation of the results. For publicly traded clubs exists a direct economic channel of their sporting success to influence their stock price, because successful teams generate higher profits and hence are more valuable (Brown and Hartzell, 2001; Gerlach, 2011). Accordingly, rational arguments might explain movements in the clubs' stock prices within a range that corresponds to the cash flow changes induced by the game. In contrast, except of firms which are connected with national teams (e.g. as a sponsor), index reactions after soccer games of national teams can hardly be justified by direct cash flow changes of firms included in the stock index. Therefore, most authors interpret abnormal return reactions after matches of national teams to be driven by investor sentiment (among others, Edmans, Garcia, and Norli, 2007).

Due to these fundamental differences between national teams and individual clubs, we split our sample into two homogeneous subsets: (1) studies examining national teams' results, (2) studies analysing the impact of individual clubs. Because of differences in study design, some moderator variables described in the following subsections can only be analysed for one of the two subsamples (see also Table 2).[12]

Regional differences

Since many studies report results for multi-country data sets, e.g. Edmans, Garcia and Norli (2007) investigate soccer matches from 39 countries, a major proportion of estimates cannot be clearly assigned to a single country. To still capture regional differences, we code four dummy variables indicating whether a study includes matches of the main FIFA[13] continental championships (Asian Cup, Copa América, European Championship)[14] or the FIFA World Cup (omitted base category).

For the sample of individual clubs, a clustering based on world regions is meaningless as more than 95% of the observations include matches from European countries. Thus, we decided to introduce another moderator variable indicating whether a study examines clubs from one of the four major European soccer nations (England, Italy, Germany and Spain).[15]

Match-related study characteristics

To control for match-related differences, a moderator (*important games*) is equal to one if an observed return estimate refers to knock-out games[16] or final games of national teams, or to games in the UEFA Champions League, Euro League or relegation and promotion matches of individual clubs. This variable is motivated by the argument that soccer matches are of different importance and thus should trigger different stock market reactions (Edmans, Garcia, and Norli, 2007). To capture the surprise effect (among others, Palomino, Renneboog, and Zhang, 2009), another dummy (*unexpected outcome*) takes a value of one if an estimate refers to an unexpected match result (e.g. if betting odds expect a win, however the actual result is a loss).[17] This dummy variable can only be coded if a primary study reports separate results for unexpected match outcomes. A further variable captures the venue effect (among others, Benkraiem, Louhichi, and Marques, 2009) and shows if an estimate explicitly refers to matches played on the home ground (*home games*) or the opponent's ground (*away games*). The omitted control group is a dummy variable identifying studies, which do not account for differences in the playing ground.

[12] It should be noted that also the expected sign of the moderator variables might be different for the two subgroups.
[13] The Fédération Internationale de Football Association is the world soccer association.
[14] None of the studies in our sample include matches of the other FIFA continental cups (Africa Cup, North America Cup or Nations Cup).
[15] The selection of the top soccer nations follows Edmans, Garcia and Norli (2007), who analyse seven nations as top soccer countries. Due to missing observations for individual clubs from Argentina, Brazil or France, we had to exclude three of the seven nations from the classification.
[16] Knock-out games are defined as games after the group session in national cups like the FIFA World Cup.
[17] Primary studies typically measure market expectations by the implicit probabilities observed from betting markets.

Table 2. Variable definition and descriptive statistics.

		Panel A: National teams				Panel B: Individual clubs			
		Wins		Losses		Wins		Losses	
Variables	Description	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Effect	The return estimate reported in the primary study	−0.05	0.51	−0.33	0.42	0.62	2.60	−0.98	2.24
SE	The SE of the return estimate	0.42	1.35	0.47	1.61	0.53	0.83	0.63	0.76
Regional differences									
Asian Cup[a]	1 If the estimate's sample includes matches from the Asian Cup	0.28	0.45	0.29	0.46				
Copa América[a]	1 If the estimate's sample includes matches from the Copa América	0.28	0.45	0.29	0.46				
UEFA Euro[a]	1 If the estimate's sample includes matches from the European Championship	0.69	0.46	0.72	0.45				
World Cup[a]	1 If the estimate's sample includes matches from the FIFA World Cup (base category)	0.64	0.48	0.66	0.48				
Top soccer league[b]	1 If the estimate's sample includes soccer clubs from England, Italy, Germany or Spain					0.35	0.48	0.39	0.49
Match-related characteristics									
Important games	1 If the estimate refers to highly important matches	0.22	0.42	0.22	0.41	0.17	0.38	0.17	0.38
Unexpected outcome	1 If the estimate refers to unexpected match results with market expectations observed from betting odds	0.02	0.12	0.06	0.24	0.11	0.32	0.11	0.31
Home games[b]	1 If the estimate refers to matches played on the club's home ground					0.05	0.21	0.04	0.20
Away games[b]	1 If the estimate refers to matches played on the opponent's ground					0.05	0.21	0.06	0.23
Mixed ground[b]	1 If the estimate does not consider differences in the playing ground (base category)					0.91	0.29	0.90	0.29
Data characteristics									
Before 2005	1 If the estimate refers to an average observation period [(End year of data − start year)/2] before 2005	0.46	0.50	0.49	0.50	0.44	0.50	0.49	0.50
Event window > 1 day after match[b]	1 If the estimate measures the return reactions at the second day after a match or a later point in time					0.24	0.43	0.25	0.43
No. of games	The logarithm of the number of games covered by the sample	3.74	1.34	3.51	1.27	4.45	1.41	4.06	1.33
Exclusion of outliers	1 If return outliers are removed from the sample	0.08	0.27	0.07	0.26	0.26	0.44	0.24	0.43
Small stocks[a]	1 If the estimate explicitly refers to companies with small market capitalization	0.06	0.24	0.06	0.25				
Large stocks[a]	1 If the estimate explicitly refers to companies with large market capitalization	0.04	0.19	0.03	0.18				
Mixed stocks[a]	1 If the estimate does not consider differences in the market capitalization of the firms (base category)	0.90	0.30	0.91	0.30				
Estimation characteristics and design of analysis									
GARCH model	1 If the estimate is derived from a GARCH-type event study model (base category: dummy regression or average abnormal return event study model)	0.10	0.30	0.09	0.29	0.12	0.33	0.11	0.32
Stock index[b]	1 If the estimate refers to abnormal returns of a stock market index (base category: returns refer to the club's stock price)					0.27	0.44	0.26	0.44
Market factor	1 If the model controls for market-wide effects	0.62	0.49	0.64	0.48	0.95	0.21	0.96	0.19
Day-of-the-week	1 If the model controls for day-of-the-week effects	0.73	0.45	0.73	0.44	0.40	0.49	0.38	0.49
Serial correlation	1 If the model controls for first-order serial correlation	0.88	0.32	0.90	0.30	0.53	0.50	0.52	0.50
Publication characteristics									
Native co-author	1 If at least one co-author is native to the country under examination	0.24	0.43	0.23	0.42	0.68	0.47	0.68	0.47
No. of citations	The logarithm of [(Google Scholar citations)/(age of the study) + 1], collected in September 2017	1.16	1.51	1.22	1.54	1.33	0.74	1.48	0.86

Variables marked with [a] are only considered in the sample of national teams. Variables marked with [b] are only considered in the sample of individual clubs.

Data characteristics

As the results for the soccer match effect might change over time, we include a dummy variable (*before 2005*) measuring whether a study's average observation period refers to the time period before 2005.[18] Another variable (*event window > 1 day after match*) indicates whether an estimate measures the return effect on the first trading day after a match or the lagged effect at a later point in time. Furthermore, we also control whether the number of games examined in the primary studies systematically affects the reported return effects (*no. of games*). A further aspect discussed in the literature concerns the size effect. If investor sentiment exists, a stronger return reaction of stocks with small market capitalization would be expected (among others, Fung et al., 2015). This effect may be reasoned by a home bias (French and Poterba, 1991). Accordingly, domestic investors are more involved in firms with small market capitalization and thus, small companies are more likely to be subject to sports sentiment. To capture the size effect, a dummy is included for the case that the reported estimates explicitly refer to small caps (*small stocks*). Another dummy is coded for large caps (*large stocks*). The omitted control group is a dummy variable indicating studies, which do not account for differences in market capitalization.

Estimation characteristics and design of analysis

To account for differences in the estimation technique, we code a dummy variable (*GARCH model*) that is equal to one if authors apply GARCH-type models to estimate Equation (1). For the subsample of individual clubs, an additional moderator (*stock index*) indicates whether the dependent variable in Equation (1) refers to a stock market index or the stock price of publicly traded clubs. As the model specification might affect the reported results, we add three dummies to control for the model setup: (1) market factor included (*market factor*),[19] (2) day-of-the-week effects included (*day-of-the-week*), (3) correction for autocorrelation (*serial correlation*).

Publication characteristics

If native authors are fans of the soccer team investigated in their study, they might be willed to see a positive return effect after wins and a weaker effect after losses. A dummy variable denotes if at least one co-author is native to the country under examination (*native co-author*). We classify authors as native, if they were born or obtained an academic degree in the country under examination. To consider aspects of study quality not captured by the data and methodology variables, we control for the number of Google Scholar citations normalized by the study's age (*no. of citations*).

V. Empirical results

National teams

Analysis of publication bias

Figure 1 shows the funnel plots for wins and losses of national teams.

For wins (Panel A), the graph appears to be rather symmetric. For lost matches (Panel B), we can observe that the majority of estimates fall into the left side of the plot, while the right side is truncated. This asymmetry serves as a first visual indication of selection for negative return reactions after losses. Accordingly, literature seems to overestimate the loss effect by systematically discarding zero and positive returns after losses. However, as visual inspections from the funnel plots are vulnerable to subjective interpretation, we continue with a statistical test of funnel plot asymmetry and thus publication bias.

The MRA model reported in Equation (2) is the most common statistical funnel asymmetry test (Egger et al., 1997).[20] The estimate for the slope coefficient (*SE*) measures the presence and size of publication bias. The constant represents the mean soccer match effects corrected for publication bias. Table 3 reports the results of the funnel asymmetry test for national teams using the four alternative estimation methods (WLS, FE, ME and WLS with alternative weights), whereas the WLS regression

[18]The break point 2005 is chosen based on a graphical analysis of the structural changes of the soccer match effects over time.

[19]For national teams, this variable is coded to be 1 if the market model includes a measure for a global market effect (e.g. MSCI world index is included in the examination of matches of the US national team on the S&P 500). For individual clubs, this variable is coded to be 1 if the market model includes a stock market index (e.g. FTSE 100 index is included in the examination of a UK soccer club's stock price).

[20]The idea of the funnel asymmetry test follows from rotating the axes of the funnel plots in Figure (1) and inverting the values on the new horizontal axis (Stanley and Doucouliagos, 2012). A significant estimate of the slope coefficient then provides formal evidence for funnel asymmetry.

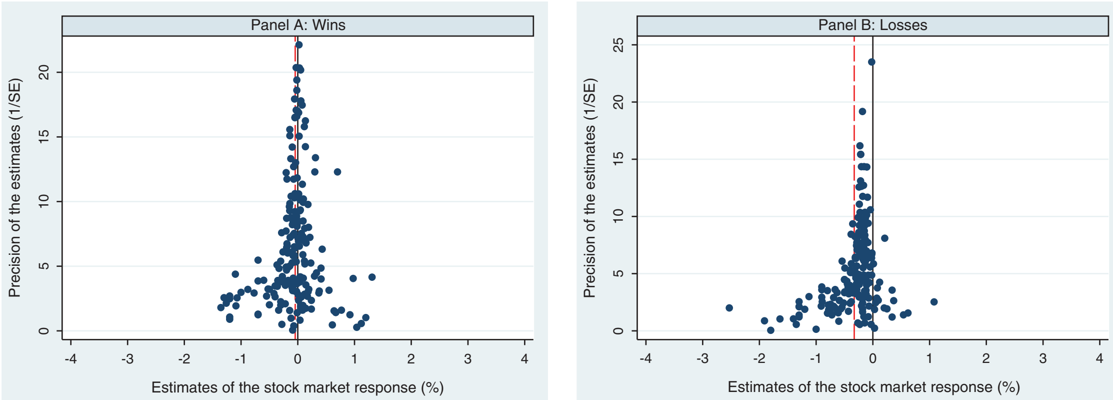

Figure 1. Funnel plots (National teams).

In the absence of publication selection, the funnels should be symmetrically distributed around the most precise estimates, which are clustered around the top of the funnel. The dashed lines in red show the sample means.

(model 1) represents our baseline model. The other three models serve as a robustness test. For the interpretation in the following sections, we refer to the results from the baseline models.

The statistical tests of publication bias underline the previous suspicion from the funnel plots. For wins (Panel A), there is neither evidence for publication bias nor a significant mean soccer match effect after correcting for selective reporting. In contrast, the bias coefficient in the subsample of lost matches (Panel B) is statistically significant ($\hat{\beta}_{SE} = -1.0181$; $p < 0.01$; model 1b). The negative sign of the coefficient suggests that there is a preference in the literature to report strong loss effects and to omit zero or positive stock market responses. Regarding the extent of publication bias, we follow the guidelines by Doucouliagos and Stanley (2013) and classify the estimate of $\hat{\beta}_{SE}$, which is larger than 1, as 'substantial selectivity'.[21] When looking at the estimate for the intercept, it becomes apparent that the mean soccer match effect corrected for publication bias is about − 5 basis points ($\hat{\beta}_0 = -0.0464$; $p > 0.05$; model 1b). Nevertheless, this effect is insignificant. As there is no loss effect after correcting for publication bias, our meta-analysis results are in line with Klein, Zwergel and Fock (2009). This contradicts with previous studies interpreting significant index movements after soccer games of national teams as evidence for sports sentiment (among others, Ashton, Gerrard, and Hudson, 2011; Edmans, Garcia, and Norli, 2007). The findings are robust across the different MRA specifications (models 2–4).

The magnitude of publication bias can also be illustrated by comparing the uncorrected average effects (reported in Table 2) with the corrected effects represented by the intercept values in Table 3. For wins, the arithmetic average is − 5 basis points. After correction for publication selection, the estimate becomes positive with a value of 4 basis points in the baseline model (1a). Therefore, it seems questionable why the arithmetic average effect for wins is negative. Under the rationality paradigm, we would expect a zero effect and under the sports sentiment hypothesis, we would expect stock returns to rise due to a positive mood effect. One possible explanation for this result might be that most primary studies measure wins and losses in the same model (see Equation 1). If researchers search for negative loss effects as evidence for sports sentiment and therefore adjust their models until they find a significant loss effect, also the estimates of the win coefficient in Equation (1) might be biased downwards. The funnel plot of the win effects (Figure 1) endorses this assumption. If authors would prefer positive win effects, we would expect more estimates to fall into the right side of the plot. However, the funnel appears at least symmetric or there is even a slightly larger proportion of dots in the left side of the funnel.

[21]According to Doucouliagos and Stanley (2013), publication bias can be classified as 'little to modest' if the bias coefficient is statistically insignificant or $|\hat{\beta}_{SE}| < 1$; 'substantial' if $\hat{\beta}_{SE}$ is statistically significant and $1 \leq |\hat{\beta}_{SE}| \leq 2$; and 'severe' if $\hat{\beta}_{SE}$ is statistically significant and $|\hat{\beta}_{SE}| > 2$. These guidelines hold for the test of publication bias without including further moderator variables (Equation 2).

Table 3. Test of publication bias and true effect beyond (National teams).

	Panel A: Wins				Panel B: Losses			
	(1a) WLS (baseline)	(2a) FE	(3a) ME	(4a) WLS (alt. weights)	(1b) WLS (baseline)	(2b) FE	(3b) ME	(4b) WLS (alt. weights)
SE	−0.4356	−0.2025	−0.4173	−0.3175	−1.0181***	−1.0501***	−0.8642***	−1.1720***
(publication bias)	(−1.31)	(−0.56)	(−1.25)	(−0.97)	(−8.01)	(−5.36)	(−6.79)	(−8.30)
Constant	0.0407	0.0057	0.0282	0.0422	−0.0464	−0.0410	−0.073	−0.0302
(effect beyond bias)	(0.91)	(0.11)	(0.64)	(1.51)	(−1.00)	(−1.25)	(−1.64)	(−1.25)
Adj. R^2	0.02	–	0.04	0.02	0.33	–	0.60	0.43
No. of estimates	196				202			
No. of studies	11				10			

The table presents the results of the meta-regression model from Equation (2) for all studies including estimates for the soccer match effect of national teams. The estimates for *SE* measure the presence and degree of publication bias. The constant quantifies the true soccer match effect corrected for publication bias. Estimations in models (1)–(3) are conducted by weighted least squares with the inverse of the estimates' SEs used as weights to correct for heteroscedasticity. Model (2) additionally incorporates study-level fixed effects to consider unobservable heterogeneity. Model (3) is a mixed effects model with random study-level effects estimated by maximum likelihood. Model (4) applies alternative weights (inverse of estimates' SEs multiplied with the inverse number of estimates observed from a study) to avoid a dominating influence of studies reporting a high number of estimates. For all models, SEs are clustered at the study-level to account for within-study dependencies arising from multiple estimates reported in the same study. *t*-statistics are reported in parentheses.

*** Denotes significance at the 1% level.

For losses of national teams, the arithmetic average is − 33 basis points. Comparing this value with the corrected mean effect of the baseline model (1b) reveals that, due to publication bias, the mean effect is exaggerated by a factor close to 7.

Beside the existence of a significant return reaction, literature often interprets differences in the size of the effects after wins and losses as indicator for non-rational investor behaviour. The asymmetry effect refers to larger absolute values for $\hat{\beta}_L$ compared to $\hat{\beta}_w$ in Equation (1). This phenomenon can be explained by the fact that people's reference point is that their team wins,[22] which causes biased ex ante expectations for the match outcome, which are corrected after the game result is known (Edmans, Garcia, and Norli, 2007). Regarding the findings from Table 3, we cannot find any evidence for an asymmetry in the sample of national teams. Hence, the strong asymmetry effect that can be observed from the simple average effects (Table 1) vanishes after correcting for publication bias. This serves as further evidence against the sports sentiment hypothesis.

Analysis of heterogeneity

As we can see from the study overview in Table 1, estimates for the soccer match effect substantially differ both within and between studies. In this section, we attempt to relate the differences in the estimates to differences in the design of the primary studies. Table 4 reports the results of the multiple MRA model (Equation 3), where the models (5a) and (5b) represent our baseline for interpretation. The other two models (ME and WLS with alternative weights) serve as a robustness test. It should be noted that, in contrast to the basic MRA (Equation 2), the estimated values of the intercept cannot be directly interpreted as mean soccer match effect, because they are now conditional on the values of the moderators. Hence, there is a wide range of mean values, depending on the desired conditions and the resultant variable manifestations. Consequently, for the multiple MRA model, we do not interpret the results of the intercept term.

Regarding the results for $\hat{\beta}_{SE}$, we find in the baseline model (5b) that even after controlling for various aspects of study design, the bias coefficient in the subsample of lost games of national teams still shows significant evidence for publication bias. As the guidelines for the interpretation of the bias coefficient by Doucouliagos and Stanley (2013) refer to the case without including additional moderator variables, they cannot be applied equivalently to the model including further variables. However, the primary goal of the multiple MRA model is not the test of publication bias, but rather the analysis of residual heterogeneity beyond publication bias.

For wins (Panel A), the results of the additional moderator variables are weak. Therefore, we conclude that the heterogeneity of the estimates in the funnel plot is largely driven by random variability. Regarding the subsample of lost matches (Panel B),

[22]Bernile and Lyandres (2011) show that investors overestimate the winning probability by nearly 5 percentage points.

Table 4. Multiple meta-regression results (National teams).

	Panel A: Wins			*Panel B: Losses*		
	(5a) WLS (baseline)	(6a) ME	(7a) WLS (alt. weights)	(5b) WLS (baseline)	(6b) ME	(7b) WLS (alt. weights)
Constant	−0.3404	−0.4482	−0.3211	−0.2242	−0.2010	−0.2291
	(−1.10)	(−1.35)	(−1.22)	(−1.63)	(−1.47)	(−1.26)
SE (publication bias)	0.0610	0.2136	0.1237	−0.6079**	−0.6037**	−0.7682**
	(0.18)	(0.60)	(0.45)	(−2.96)	(−2.93)	(−2.86)
Asia Cup	−0.0149	0.0142	−0.0447	−0.0262	−0.0302	−0.0664
	(−0.31)	(0.24)	(−0.68)	(−1.27)	(−1.27)	(−1.38)
Copa América	0.0851	0.0837	0.1876	0.0292	0.0284	−0.0151
	(1.11)	(0.89)	(1.45)	(1.14)	(1.01)	(−0.21)
UEFA Euro	−0.0464	−0.0734	−0.0658	0.0219	0.0255	0.1252
	(−0.68)	(−1.02)	(−0.91)	(0.25)	(0.28)	(1.00)
Important games	0.0416	−0.0025	−0.0094	0.0060	0.0066	0.0305
	(0.67)	(−0.03)	(−0.10)	(0.15)	(0.16)	(0.52)
Unexpected outcome	0.2744	0.3079*	0.2702	−0.0177	−0.0156	0.0044
	(1.55)	(1.91)	(1.71)	(−1.29)	(−1.04)	(0.19)
Before 2005	−0.0903	0.0036	−0.0826	−0.1065**	−0.1435**	−0.1164*
	(−0.48)	(0.02)	(−0.89)	(−3.01)	(−2.92)	(−1.92)
No. of games	0.0309	0.0399	0.0180	0.0039	−0.0002	−0.0015
	(0.78)	(0.85)	(0.47)	(0.30)	(−0.02)	(−0.09)
Exclusion of outliers	−0.0159	−0.0096	−0.0323	−0.0082	−0.0096	−0.0362
	(−0.75)	(−0.32)	(−0.84)	(−0.41)	(−0.44)	(−0.98)
Small stocks	−0.0662	−0.0609	−0.0117	−0.1912*	−0.1877*	−0.1919
	(−0.57)	(−0.45)	(−0.09)	(−2.15)	(−2.10)	(−1.78)
Large stocks	0.0075	−0.0220	−0.0287	0.0863***	0.0884***	0.1023***
	(0.20)	(−0.34)	(−0.38)	(6.49)	(6.29)	(3.80)
GARCH model	0.0064	−0.0346	−0.0443	−0.2546**	−0.2412**	−0.1048
	(0.03)	(−0.27)	(−0.50)	(−2.68)	(−2.88)	(−0.73)
Market factor	0.1684	0.1657	0.1246	0.1159	0.1397	0.1334
	(1.25)	(1.25)	(1.27)	(1.47)	(1.79)	(1.35)
Day-of-the-week	−0.2326	−0.2448	−0.2662*	−0.2088**	−0.2170**	−0.1100
	(−1.04)	(−1.37)	(−2.04)	(−2.86)	(−2.99)	(−1.22)
Serial correlation	0.1688	0.2072	0.2383	0.1914**	0.1744*	0.1012
	(0.78)	(1.22)	(1.78)	(2.29)	(1.89)	(0.75)
Native co-author	0.2980	0.2909	0.3178**	0.1888**	0.2030**	0.0976
	(1.31)	(1.63)	(2.29)	(2.52)	(2.83)	(0.80)
No. of citations	0.0210	0.0109	0.0212	0.0055	0.0145	0.0062
	(0.46)	(0.30)	(1.07)	(0.56)	(1.10)	(0.35)
Adj. R^2	0.18	0.16	0.23	0.52	0.70	0.58
No. of estimates		196			202	
No. of studies		11			10	

The table presents the results of the meta-regression model from Equation (3) for all studies including estimates for the soccer match effect of national teams. Explanatory variables and descriptive statistics are reported in Table 2. Estimations in models (5) and (6) are conducted by weighted least squares with the inverse of the estimates' SEs used as weights to correct for heteroscedasticity. Model (6) is a mixed effects model with random study-level effects estimated by maximum likelihood. Model (7) applies alterative weights (inverse of estimates' SEs multiplied with the inverse number of estimates observed from a study) to avoid a dominating influence of studies reporting a high number of estimates. For all models, SEs are clustered at the study-level to account for within-study dependencies arising from multiple estimates reported in the same study. *t*-statistics are reported in parentheses.
***, **, *Denote significance at the 1%, 5% and 10% level.

several interesting findings can be observed. The time dummy (*before 2005*) indicates that the size of the negative loss effect is, on average, − 11 basis points larger compared to studies examining games in more recent time periods. This serves as evidence that the loss effect decreases over time, which is in line with the finding by Ashton, Gerrard and Hudson (2011). Moreover, the positive and significant coefficients for the *large stocks* variable imply that the negative loss effect is reduced by 9 basis points for estimates referring to stocks with large market capitalization. Previous studies support the finding that large stocks are less affected by investor sentiment (Baker and Wurgler, 2006). Furthermore, the method choice seems to have an impact on the reported results. GARCH-type regressions find more negative loss effects (about − 25 basis points) compared to studies applying regression-based event studies via OLS or simple average abnormal return models. Furthermore, if authors correct their estimation for day-of-the-week effects (serial correlation), they find, on average, − 21 basis points larger (19 basis points smaller) negative loss effects. Finally, the dummy variable *native co-author* reveals that the nationality of the authors systematically influences their findings, i.e. native authors tend to report that lost matches of national teams have a less negative impact of about 19 basis points.

With respect to the robustness of the findings for the moderator variables, the ME models (6a and 6b) support the inferences from the baseline models. The WLS models with alternative weights (7a and 7b) produces different results. For wins, there is some evidence that the nationally of the authors increases the win effect. For losses, most of the effects disappear and only the *large stocks* variable shows significance.

Regarding the overall fit of the models represented by the adjusted R^2 statistics, the correction for publication bias and the inclusion of the moderator variables helps to explain 18% (52%) of the variation in the existing research results for wins (losses) of national teams. In comparison, Nelson and Kennedy (2009) find that, in the field of economics, the median adjusted R^2 statistics across 125 previous meta-analyses is 44%.

Individual clubs

Analysis of publication bias

Figure 2 shows the funnel plots for the sample of individual clubs.

In both graphs, we observe larger variability of the estimates compared to the funnel plots of national teams. The estimates for the win effect (Panel A) seem quite symmetrically distributed around the most precise estimates. In contrast, in the plot for lost matches (Panel B), there are many estimates with low precision dispersed around the bottom and only few estimates with high precision that are close to zero. Again, the plot indicates that there might be a tendency to report negative loss effects. However, this interpretation is subjective. Therefore, we continue with the results of the statistical funnel asymmetry test (Equation 2), which are reported in Table 5.

For wins (Panel A), there is some evidence for a tendency of authors to prefer reporting positive stock market returns. $\hat{\beta}_{SE}$ shows significance at least at 10% in the baseline model (8a) with a t-statistic of 1.93. Thus, publication bias cannot be neglected for wins, although evidence is weak. This is supported by the fact that the magnitude of the bias coefficient is 1.020. According to Doucouliagos and Stanley (2013), this finding can be interpreted as 'substantial selectivity'. After correcting the mean soccer match effect after wins for publication selection, we find an insignificant mean return, which is illustrated by the coefficient of the constant term ($\hat{\beta}_0 = 0.0615$; $p > 0.05$; Model 8a). This effect is about 10 times smaller than the simple average, which accounts for 62 basis points. The alternative models support the evidence for publication bias (models 9a and 11a) and the non-existence of a significant mean return after wins of individual clubs (models 9a, 10a and 11a).

In Panel B, the baseline model suggests no presence of publication bias. According to the results for the intercept, the mean effect corrected for publication bias is significant ($\hat{\beta}_0 = -0.3876$; $p < 0.05$; model 8b), which implies that there is a negative stock market response to losses of individual clubs. Compared to the simple average, which accounts for − 98 basis points (see Table 2), publication bias causes an overestimation

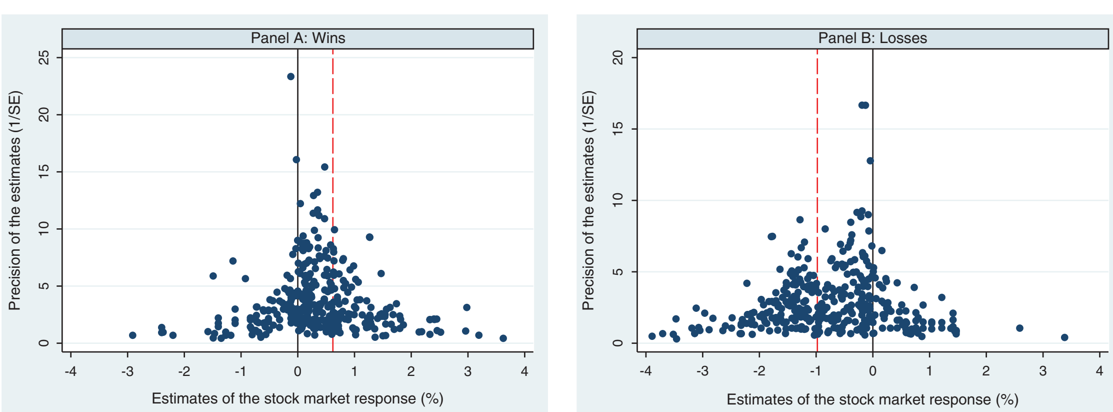

Figure 2. Funnel plots (individual clubs).

In the absence of publication selection, the funnels should be symmetrically distributed around the most precise estimates, which are clustered around the top of the funnel. The dashed lines in red show the sample means.

Table 5. Test of publication bias and true effect beyond (individual clubs).

	Panel A: Wins				Panel B: Losses			
	(8a) WLS (baseline)	(9a) FE	(10a) ME	(11a) WLS (alt. weights)	(8b) WLS (baseline)	(9b) FE	(10b) ME	(11b) WLS (alt. weights)
SE	1.0201*	0.8297**	0.5691	1.2246*	−0.9905	−1.0827**	−0.5517	−1.9826***
(publication bias)	(1.93)	(2.70)	(1.20)	(1.91)	(−1.49)	(−2.58)	(−0.93)	(−4.89)
Constant	0.0615	0.1075	0.5691	−0.0022	−0.3876**	−0.3550**	−0.5229**	−0.0538
(effect beyond bias)	(0.96)	(1.45)	(1.20)	(−0.11)	(−2.45)	(−2.39)	(−2.34)	(−0.99)
Adj. R^2	0.10	–	0.15	0.09	0.11	–	0.34	0.30
No. of estimates	352				376			
No. of studies	24				24			

The table presents the results of the meta-regression model from Equation (2) for all studies including estimates for the soccer match effect of individual clubs. The estimates for *SE* measure the presence and degree of publication bias. The constant quantifies the true soccer match effect corrected for publication bias. Estimations in models (1)–(3) are conducted by weighted least squares with the inverse of the estimates' SEs used as weights to correct for heteroscedasticity. Model (2) additionally incorporates study-level fixed effects to consider unobservable heterogeneity. Model (3) is a mixed effects model with random study-level effects estimated by maximum likelihood. Model (4) applies alternative weights (inverse of estimates' SEs multiplied with the inverse number of estimates observed from a study) to avoid a dominating influence of studies reporting a high number of estimates. For all models, SEs are clustered at the study-level to account for within-study dependencies arising from multiple estimates reported in the same study. *t*-statistics are reported in parentheses.

***, **, *Denote significance at the 1%, 5% and 10% level.

that is about twice as large as the uncorrected mean. However, even after correction, the effect is still remarkably different from zero. The finding of a negative loss effect is in line with two of the three alternative models (9b and 10b). In contrast, models (9b) and (11b) show strong evidence for publication bias with coefficients above 1. In summary, there is no clear picture regarding the estimates of the bias coefficient.

Comparing the results for the mean returns after wins and losses exhibits a strong asymmetry effect for individual clubs. This finding is consistent with past studies documenting asymmetry in stock market responses between good and bad news (Dimic et al., 2017; Scholtens and Peenstra, 2009). Edmans, Garcia and Norli (2007) explain this finding by the asymmetric structure of international competitions. For example, a loss in a second leg match in the round of the last 16 in the UEFA Champions League leads to the elimination of a team, which offers information to investors that the club will not earn additional price money from this tournament in the current season. In contrast, a win in this knock-out game merely pushes a team to the next round of the competition. Altogether, the existence of an asymmetry effect is a challenge for market efficiency and thus might be interpreted as evidence for sports sentiment (Bernile and Lyandres, 2011).

Analysis of heterogeneity

Table 6 reports the results of the extended MRA model (Equation 3) including additional variables that are suspected to be in charge of the large variation of soccer match estimates across studies.

The estimates for the bias coefficient $\hat{\beta}_{SE}$ indicate selective reporting after wins (Panel A) and losses (Panel B). Accordingly, publication bias is detected even when we include different aspects of study design.

Regarding the moderator variables, we can conclude for wins (Panel A) that studies examining clubs from one of the top four soccer nations report, on average, smaller loss effects of -51 basis points in the baseline model (12a). This result is somewhat challenging, as other studies find that return effects are stronger in countries in which soccer is most popular and of large economic importance (e.g. Edmans, Garcia, and Norli, 2007). If the return reaction to club matches is driven by sports sentiment, our results indicate that this sentiment-driven reaction is less pronounced in the top soccer nations. As the coefficient for the time dummy (*before 2005*) is positive and statistically significant for wins, there seems to be a tendency for larger win effects in the 1990s and earlier 2000s. The estimate for the *stock index* variable is also significant, i.e. studies examining the impact of individual clubs on stock indices find lower returns after wins than authors focusing on the reaction of the clubs' stock price. According to the baseline Model (12a), the index effect is about 74 basis points smaller. Moreover, studies controlling for serial correlation in their event study find stronger win effects.

In Panel B, the coefficient for *home games* provides strong evidence that losses on the home ground increase the negative loss effect by -35 basis points.

Table 6. Multiple meta-regression results (individual clubs).

	Panel A: Wins			*Panel B: Losses*		
	(12a) WLS (baseline)	(13a) ME	(14a) WLS (alt. weights)	(12b) WLS (baseline)	(13b) ME	(14b) WLS (alt. weights)
Constant	−0.1891	−0.4684	−0.0897	0.3915	0.7503	0.1151
	(−0.73)	(−1.08)	(−0.38)	(0.93)	(1.14)	(0.29)
SE (publication bias)	1.1441**	1.0366**	0.9770	−1.2765**	−1.0543**	−1.5758***
	(2.46)	(2.17)	(1.43)	(−2.45)	(−2.37)	(−4.73)
Top soccer league	−0.5060***	−0.1445	−0.6047***	0.3089*	0.2941	0.4451***
	(−2.82)	(−0.46)	(−5.81)	(1.75)	(1.29)	(5.13)
Important games	−0.1885	−0.0849	−0.1160	−0.2619	−0.2676	−0.1048
	(−1.41)	(−0.46)	(−1.01)	(−1.55)	(−1.42)	(−1.05)
Unexpected outcome	0.0431	0.0194	−0.1810	0.0292	−0.0290	0.5690
	(0.17)	(0.09)	(−1.04)	(0.21)	(−0.16)	(1.45)
Home games	−0.1068	−0.1873**	0.0868	−0.3538***	−0.2928	−0.3303
	(−1.41)	(−2.28)	(0.91)	(−2.94)	(−1.57)	(−1.70)
Away games	0.0362	0.0589	0.1389	−0.0484	0.0692	0.0218
	(0.53)	(0.77)	(1.12)	(−0.56)	(0.57)	(0.12)
Before 2005	0.4041***	0.1846	0.5142***	0.2329	0.1477	−0.0534
	(3.18)	(0.60)	(3.81)	(0.88)	(0.65)	(−0.22)
Event window >1 day after match	−0.2437	−0.3957**	−0.1284	0.2368	0.2288	0.1058
	(−1.42)	(−2.41)	(−0.98)	(0.95)	(0.76)	(0.73)
No. of games	0.0715	0.0564	0.0916*	−0.2009***	−0.1454	−0.1767***
	(1.20)	(0.89)	(1.96)	(−3.36)	(−1.66)	(−3.02)
Exclusion of outliers	−0.4475*	−0.9917*	0.0155	1.1705***	1.5695***	0.6281*
	(−1.79)	(−2.03)	(0.05)	(3.37)	(4.37)	(2.05)
GARCH model	−0.0376	−0.0031	−0.1785	0.1071	−0.4201***	0.1365
	(−0.45)	(−0.03)	(−1.26)	(0.93)	(−4.13)	(0.88)
Stock index	−0.7399***	−0.4059	−1.0698***	0.1912	0.3768	0.2081
	(−3.18)	(−0.67)	(−6.11)	(0.66)	(1.25)	(0.54)
Market factor	−0.0748	0.3235	−0.5770***	0.1162	−0.4908	0.4562***
	(−0.34)	(0.79)	(−2.81)	(0.48)	(−1.67)	(3.85)
Day-of-the-week	0.2977*	0.4525**	0.4400***	−0.3675*	−0.5163**	−0.3264
	(1.88)	(2.25)	(3.17)	(−1.77)	(−2.41)	(−0.93)
Serial correlation	0.3556**	0.4519**	0.0490	0.1288	0.1621	0.4863***
	(2.79)	(2.22)	(0.53)	(0.75)	(0.80)	(3.33)
Native co-author	0.2362	−0.0841	0.5578***	−0.4487**	−0.4625***	−0.3136*
	(1.09)	(−0.37)	(3.52)	(−2.46)	(−2.94)	(−1.95)
No. of citations	−0.1381	−0.0245	0.0020	−0.0443	−0.0795	−0.1525*
	(−1.31)	(−0.21)	(0.03)	(−0.65)	(−0.91)	(−1.86)
Adj. R^2	0.33	0.30	0.39	0.41	0.53	0.48
No. of estimates		352			376	
No. of studies		24			24	

The table presents the results of the meta-regression model from Equation (3) for all studies including estimates for the soccer match effect of individual clubs. Explanatory variables and descriptive statistics are reported in Table 2. Estimations in models (5) and (6) are conducted by weighted least squares with the inverse of the estimates' SEs used as weights to correct for heteroscedasticity. Model (6) is a mixed effects model with random study-level effects estimated by maximum likelihood. Model (7) applies alterative weights (inverse of estimates' SEs multiplied with the inverse number of estimates observed from a study) to avoid a dominating influence of studies reporting a high number of estimates. For all models, SEs are clustered at the study-level to account for within-study dependencies arising from multiple estimates reported in the same study. *t*-statistics are reported in parentheses.
***, **, *Denote significance at the 1%, 5% and 10% level.

If markets are efficient, we would expect no overall difference between home and away games. Thus, the result might be interpreted as further evidence for mood-related investor behaviour (Bernile and Lyandres, 2011). Also, the number of games explains differences across studies. According to the baseline model (12b), studies with more matches in their sample (*no. of games*) report loss effects that are, on average, – 20 basis points smaller than studies with fewer games in their sample. There is also evidence that the *exclusion of outliers* systematically produces less negative loss effects. This finding is intuitive, as the exclusion of extreme observations reduces the chance to find large effects. From the coefficient for *native co-author*, we might conclude that authors, who are native to the country under examination, tend to report more negative loss effects. The negative sign of the coefficient implies that native authors favour more pronounced return reactions of clubs. The direction of this effect is different for national teams and individual clubs.

From the two alternative models, we can derive for Panel A that there is additional support in at least one of the robustness tests for the effects identified for the variables *top soccer league*, *before 2005* and *stock index*. In addition to the baseline model, the alternative models (13a and 14a) suggest that controlling for day-of-the-week effects leads to stronger return reactions after wins. In Panel B, we find indication for the robustness of the results for *no. of games*, *exclusion of outliers* and *native co-author*.

In summary, the overall fit of the models shows that the correction for publication bias and the inclusion of the moderator variables explain 33% (41%) of the variation in the existing research results of wins (losses), compared to 10% (11%) in the basic MRA without controlling for the moderator variables (see Table 5).

VI. Conclusions

This study applies MRA to integrate and systematically analyse 37 empirical studies on the impact of soccer matches on stock returns. Our results reveal that literature suffers from severe publication bias, especially when looking at stock returns after lost matches. Accordingly, positive and insignificant estimates of the loss effect are less frequently reported, because researchers prefer to find a significant negative loss effect, which often serves as evidence for the existence of a sports sentiment effect and thus behavioural aspects in asset pricing. After correcting for publication bias, we find that the mean return effect of national teams is statistically insignificant for both wins and losses. This result provides evidence against the hypothesis that stock markets are driven by sports sentiment. For individual clubs, losses are associated with significantly negative postgame returns, while wins are followed by near zero returns. This asymmetry in the stock market response of individual clubs might be interpreted as an indicator for non-rational investor behaviour.

Besides the analysis of publication bias, we conduct a multiple MRA and identify various aspects of study design like regional differences in the data set, time period under examination and the design of empirical analysis to explain the wide variation in previous study outcomes. Two effects are especially strong: first, the return effects after losses of national teams and wins of individual clubs are larger for the time before 2005; second, stock market reactions after matches of individual clubs are systematically lower in the top soccer nations (England, Germany, Italy and Spain).

In summary, the selective reporting of strong and significant negative returns after losses distorts the view about the true underlying effect. If the simple average across studies, which is uncorrected for publication bias, represents the common impression about the impact of soccer games on stock markets, our analysis uncovers that this view is highly exaggerated. These findings should be considered for future analyses on the relationship between soccer matches and stock markets in particular and sports sentiment in general.

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ORCID

Jerome Geyer-Klingeberg http://orcid.org/0000-0001-6615-7439

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