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ARE SPORTS BETTING MARKETS SEMISTRONG EFFICIENT? EVIDENCE FROM THE COVID-19 PANDEMIC

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Abstract

This paper examines whether sports betting markets are semistrong-form efficient—i.e., whether new information is rapidly and completely incorporated into betting prices. We use the news of ghost matches in the top European football leagues due to the COVID-19 pandemic as the arrival of public information. Because spectators are absent in ghost games, the home field advantage is reduced, and we test whether this information is fully reflected in betting prices. Our results show that bookmakers systematically overestimate a home team's winning probability during the first period of the ghost games, which suggests that betting markets are, at least temporally, not semistrong-form efficient. We exploit a betting strategy that yields a positive net payoff over more than one month.

Keywords

Sports Betting Market, Market Efficiency, Home Advantage, COVID-19

JEL Classification

G14, L83, Z2

1. INTRODUCTION

There has been an ongoing debate in the empirical literature as to what extent information markets are efficient. Drawing from the well-established framework developed by Eugen Fama in 1970, market efficiency may be categorized into a weak, semistrong or strong form depending on the amount of information that is reflected in prices. Increasingly, empirical studies utilize betting markets to assess the information efficiency of markets: They offer economists an ideal setting to examine how information efficiency operates compared to traditional stock markets, which, due to structural characteristics, have some serious drawbacks (Croxson & Reade, 2014). From an economic perspective, betting markets, which have already become much larger than their underlying sports markets by orders of magnitude, are crucial and continue to surge in popularity with the digital revolution in full swing.

Despite an increasing strand of research on betting markets, evidence regarding the degree to which these markets are efficient is mixed, as Angelini & De Angelis (2019) highlight. The bulk of studies on information efficiency focuses on the weak form of information efficiency, while evidence of the semistrong form is scarce (Bernardo et al., 2019). A major obstacle remains in terms of cleanly assessing the arrival of new public information in semistrong market efficiency studies. In this paper, we are able to tackle this issue by using a natural experiment. In early 2020, the outbreak of COVID-19 suddenly brought the sports world and public life in general to a standstill for several months. It was not surprising that banning large sport events, which potentially are infectious epicenters, was one of the first preventive measures of governments to restrict further spreading of the virus. The situation in Europe eased over the course of the next few months, which allowed football leagues to gradually resume operations. However, none of the top European football leagues allowed spectators in their stadiums. It is established that spectators are mostly supporters of the home team, which contributes to an increased home-team winning probability, an effect called the home advantage (Goumas, 2014; Nevill et al., 1996; Pollard, 2006; Ponzo & Scoppa, 2018).

The news of "ghost games" can be considered a clean arrival of new public information: The decision was published well before resuming the league games after approval of hygiene concepts by the respective governments. Moreover, the information that teams have to play in empty stadia is highly relevant because the absence of supporters substantially reduces the home field advantage (Pettersson-Lidbom & Priks, 2010; Ponzo & Scoppa, 2018). As such, the COVID-19-induced ghost games provide an ideal setting to properly analyze the hypothesis of semistrong market efficiency in European professional soccer: To what extent is the arrival of new public information, i.e., ghost games without spectators and thus a reduced home advantage, reflected in betting odds?

We investigate soccer games played with and without closed gates in the final quarter of the 2019/2020 season. In particular, we analyze 1,446 games in the most prominent European soccer leagues in Italy, Germany, England and Spain.[1] We find that bookmakers systematically overestimated the home team's winning chances during COVID-19-induced ghost games, while bookmaker odds show no bias during the games prior to the lockdown. The results suggest that betting markets are not efficient, at least not in semistrong form. However, we also find that this inefficiency gradually decreases over time. After approximately 30 days, the impact of ghost games on the home advantage is fully incorporated into betting odds.

We contribute to the existing literature in several ways. We utilize a research design where new public information about the relative playing strength of home and away teams cleanly arrives in the market. Thus, our findings complement a yet-inconclusive strand about semistrong market efficiency in betting markets. The fact that these markets are weak-form efficient at most indicates that they provide ample opportunities for investors to earn abnormal returns by quickly reacting to surprise announcements and disclosures. Indeed, we document cumulative positive betting returns for over a month achieved through a simple betting strategy.

The remainder of this paper is structured as follows. The related literature is discussed in the second section, followed by an overview of the home advantage in section three. In the fourth section, we present the research design and the data utilized. In the fifth section, we carry out an empirical analysis and present the results. The sixth section concludes the paper.

[1] We excluded France, as the French League 1 schedule was terminated without playing ghost games.

2. MARKET EFFICIENCY & BETTING MARKETS

The question of how markets incorporate the arrival of new information has long been of interest for both practitioners and academics. In 1970, Eugene Fama developed his famous framework for market efficiency. He distinguished between three forms of market efficiency based on the available information that is reflected in market prices: weak, semistrong and strong. The possibilities to earn abnormal profits and the corresponding roles of investors highly depend on the form of market efficiency. There is literally no business for investors in strong-form efficient markets because prices fully reflect all public and private information, eroding any possibility to earn abnormal profits. While trading on nonpublic information becomes an option in semistrong-efficient markets, investment based on the analysis of public company disclosures or surprise announcements will not yield investors abnormal returns. In weak-form efficient markets, investment based on quick reactions to surprise announcements and new company disclosures may be a path to abnormal returns because market prices only incorporate historical information. Those investors trading based on technical analyses of historical prices of securities have no chance to be successful because this information is reflected in the actual market prices. In other words, the business of "pure technicians" is limited to inefficient markets.

Given its importance for investment opportunities and investor roles, the question of market efficiency has attracted abundant empirical research. Conventional financial markets are the focus of this research, considering their significant role in the functioning of the economy as a whole. Corporate events such as stock splits (Byun & Rozeff, 2003), earnings releases (Foster et al., 1984), and merger announcements (Asquith, 1983) as well as corporate layoffs (Elayan et al., 1998), have been empirically investigated. Fama (1998) discusses market efficiency, long-term returns and apparent anomalies of corporate events. Croxson and Reade (2014) note that empirical evidence of prices updating fully and immediately, as an efficient market would require, is mixed: The authors conclude that some investigations find supporting evidence, while a number of others suggest a postnews price shift.

Due to the structural characteristics of conventional financial markets, some serious drawbacks complicate a clean test of market efficiency hypotheses, as Croxson and Reade (2014) have explained. On the one hand, it is difficult to determine when news is absorbed by the market and to rule out information leakage. On the other hand, the definition of a normal return remains obscure because the fundamental values of traditional financial products are not observable. As stock is infinitely lived, the value depends on the present value of future cash flows and on the price someone is expected to pay for security in the future, making it difficult to test for rationality in the stock market (Thaler & Ziemba, 1988). Therefore, equilibrium models become necessary to define a normal security return. Such studies suffer from the joint hypothesis problem: Rejecting market efficiency may be due to a real inefficiency in the price mechanism or because the equilibrium model is incorrect (Croxson & Reade, 2014).

To allow for a cleaner test of the market efficiency hypothesis, a growing strand of literature switched to a rather "nonconventional" financial market, the sports betting market. Vaughan Williams (2005) provides an introduction to information efficiency in betting markets. This market offers some unique features that create a sort of "laboratory setting" for studying market efficiency (Hvattum, 2013): A large number of experienced investors (bettors) with access to information and assets (betting contracts) are acting in a real market. Not only does a betting contract have a clear endpoint at which its true value is revealed, but its outcome (for instance, a draw between a home and an away team) is not affected by macroeconomic factors (for instance, international trade conflicts) or bettor expectations (Flepp et al., 2017). Hence, betting markets may offer a superior lens for efficiency studies, particularly in the case of the clean arrival of new information (Croxson & Reade, 2014).

Most of the empirical work is centered around studies investigating the weak form of market efficiency in sports betting. For instance, Kuypers (2000) identifies market inefficiencies in English football, consistent with findings from Dixon and Coles (1997), Rue and Salvesen (2000) and Dixon and Pope (2004). Goddard and Asimakopoulos (2004) find evidence of generating positive returns when betting on end-of-season games. Marshall (2009) finds that markets do not instantly converge to an efficient level when arbitrage opportunities across different bookmakers arise but within minutes, they do. Angelini and De Angelis (2019) analyze odds from 41 different bookmakers on 11 European championships and conclude that most of the European major leagues may be presumed weak-form efficient using a forecast-based approach.

Bernardo et al. (2019) highlight that in contrast to the weak form of market efficiency, the semistrong form is less extensively analyzed in the literature. Vaughan Williams (2005) concludes that the presence of the semistrong form of market efficiency in sports betting would imply that it should not be possible to exploit patterns in the returns to achieve above-average or abnormal returns. Thus, on the basis of publicly available information, the expected returns are equal, at least net of costs and risk.

Predominantly, studies of semistrong market evidence are examined in the context of horse race betting (Sung et al., 2005). However, the results of such studies are mixed and inconclusive (Cain et al., 2000; Edelman, 2003; Hausch et al., 1981; Smith, 2003; Sung et al., 2005). With respect to football, Elaad et al. (2020) test for a version of semistrong efficiency, i.e., whether there is an opportunity for bettors to achieve better returns than losing the bookmaker's profit margin. The authors find no statistically significant evidence that the overall market is inefficient. Another strand of research examines the effect of experts' predictions in the main national media, as Bernardo et al. (2019) note. Despite expert predictions being more accurate than chance, Forrest and Simmons (2000) highlight that the individual expertise that tipsters can claim to offer is limited: They fail to properly incorporate publicly available information.

A semistrong-efficient market requires prices to immediately reflect new information once it becomes public knowledge. Indeed, Croxson and Reade (2014) show with data from sports betting exchanges that prices update swiftly following a scored goal in football, indicating that betting markets seem to incorporate market news rapidly and completely. By contrast, Choi and Hui (2014) reject the hypothesis of semistrong market efficiency, using similar live soccer betting data: The authors find that prices generally underreact to normal and overreact to surprising news. Bizzozero et al. (2018) suggest that fast traders promote quick price discovery and correctly incorporate new information into prices, examining courtside trading during live tennis. Brown et al. (2018) find that social media content contains additional predictive power not included in betting prices. In particular, after significant market events, such as goals and red cards, Twitter activity may help in the interpretation of information.

In preplay betting markets, prices may not immediately incorporate the arrival of new information as an efficient market would require. Bernardo et al. (2019) find evidence that betting markets are inefficient in the semistrong form utilizing a major change in expectation about team results, i.e., when a head coach of a team is replaced. The authors find that a betting strategy that makes bettors place a proportional stake on the victory of the team that changed the coach yielded a positive return for the first four matches after replacement. Deutscher et al. (2018) find evidence of temporal market inefficiencies when betting on recently promoted teams, which typically undergo major changes in the composition of the roster following promotion. Market inefficiencies remain only at the start of the season since bookmakers have difficulty predicting the playing strength of recently promoted teams at first. Thus, bookmakers may lack reliable information during certain periods where the prediction of playing strength is particularly difficult and thus provide a source of betting inefficiencies.

3. THE ROLE OF SPECTATORS ON HOME ADVANTAGE

The phenomenon of home advantage – a term "used to describe the consistent finding that the home teams in sport competition win over 50% of the games played under a balanced home and away schedule" (Courneya & Carron, 1992, p. 13) – is very well documented in competitive sports.[2] Pollard (1986) notes that although home advantage exists for all sports, its effect is biggest for soccer – which we subsequently refer to as football. The home advantage effect was later substantiated by a meta-analysis by Jamieson (2010), who analyzed the home advantage for 10 different sports. Hence, Pollard and Gomez (2009) conclude that the advantage of playing at the home field is a worldwide phenomenon, with variation both over time and across regions.

Despite the empirical consensus, there exist several mechanisms potentially explaining why playing at the home venue benefits performance. In football, crowd support, familiarity with the stadium, territoriality and travel fatigue have been recognized as potential mechanisms and empirically investigated (van Damme & Baert, 2019). In particular, support from the crowd is considered of great importance for the home advantage (Buraimo et al., 2010; Garicano et al., 2005; Schwartz & Barsky, 1977). On the one hand, the crowd tends to stimulate players' effort, motivation and energy; on the other hand, it might subconsciously influence the referee to favor the home team as an indirect effect (van Damme & Baert, 2019). For a long time, empirical studies struggled to cleanly isolate the role of crowd support from other mechanisms as they are closely linked together and might mutually enforce each other. In a recent study, Ponza and Scoppa (2018) evaluate the relevance of crowd support in determining home advantage utilizing same-stadium derbies: Teams enjoy different levels of support from the crowd due to season-ticket holders, while all other sources of home advantage, such as travel fatigue or familiarity with the stadium, are

[2] Legaz-Arrese et al. (2013) provide an overview of home advantage in different team sports.

presumed equal for both teams. The authors find evidence of a sizeable effect of crowd support on home advantage, both through encouragement of players' performance and referee bias. They conclude that crowd support significantly contributes to home field advantage.

If crowd support is vital for the success of playing in the home venue, ghost games are expected to significantly alter the home advantage, as teams play in an empty stadium. Indeed, studies suggest that the COVID-19 pandemic, which came along with games behind closed gates, significantly altered the home field advantage (Endrich & Gesche, 2020; Fischer & Haucap, 2020; Reade & Singleton, 2020). Reade and Singleton (2020) note that the home advantage not only disappeared but also reversed in the first ghost games: In the German Bundesliga, home teams won just 32% of the matches (26 out of 82), compared with 43% in the same season before March, while away teams won 45% (37 out of 82) of the ghost games, compared with 35% in the season beforehand. The authors further note that throughout June, home advantage recovered partly, perhaps due to players becoming familiar with the lack of fans in their stadium, which is consistent with the empirical evidence of Fischer and Haucap (2020), who find a reduced home advantage in the Bundesliga. However, the effect of ghost games on home advantage decreases over time. The authors suggest that as time progresses, players adapt and get used to the new situation without a crowd. Interestingly, they do not find an effect of ghost games on home advantage in lower divisions, arguing that these teams are potentially more used to playing in half-empty stadia. Bryson et al. (2020) find that ghost games and the absence of a partisan home crowd have no effect on the likelihood of a win, the goal difference and the total goals scored utilizing a very broad dataset of 23 professional leagues and seventeen countries. Drewes et al. (2020) note that with matches behind closed doors, the distinctive stadium atmosphere with fans applauding, booing and singing is completely lost. Fischer and Haucap (2020) argue that the lack of such an atmosphere is particularly harmful for teams that are used to a full stadium.

Webb (2020) suggests that ghost games may lead players and coaches alike to adapt their behavior due to the more sterile environment, being aware that any sound or conversation will potentially be broadcast, including abusive language towards the match official, and may lead to a rebalancing of the relationship between referees, players and coaches. With respect to the referees, both Endrich and Gesche (2020) and Bryson et al. (2020) present evidence of a reduced referee bias during the games behind closed gates due to COVID-19, arguing that referees are less affectated by audiences in ghost games. This finding is consistent with prior studies: Reade et al. (2020) show that the home advantage was, on average, eroded, utilizing ghost games before the pandemic. The authors present evidence that home teams score fewer goals and that visiting players were cautioned significantly less often, indicating that referee bias towards the home team is less present. This finding is consistent with work by Pettersson-Lidbom and Priks (2010), who find that referees exhibit less home bias caused by social pressure from spectators, presenting evidence from Italian soccer matches that were played in empty stadiums due to hooligan violence.

4. RESEARCH DESIGN

An efficient betting market, at least in semistrong form, requires that betting companies fully incorporate the advantage of playing in the home venue in their betting odds and immediately update the odds once new public information is released. To test whether betting markets are semistrong efficient, we make use of a natural experiment: the COVID-19 pandemic. Our identification strategy relies on the news arrival of COVID-19-induced ghost matches in European professional football. Playing behind closed gates negatively impacts the home advantage, as any crowd support is missing (Endrich & Gesche, 2020; Fischer & Haucap, 2020; Pettersson-Lidbom & Priks, 2010; Reade et al., 2020). This phenomenon is well known not only among researchers but also among fans and the general public. Even before the German Bundesliga resumed operations, and in particular after the first match day, articles drew attention to the disappearance, or at least the reduction, of the home advantage.[3] Thus, the pandemic provides a clean setting of the home advantage being exogenously altered and new public information arriving in the market.

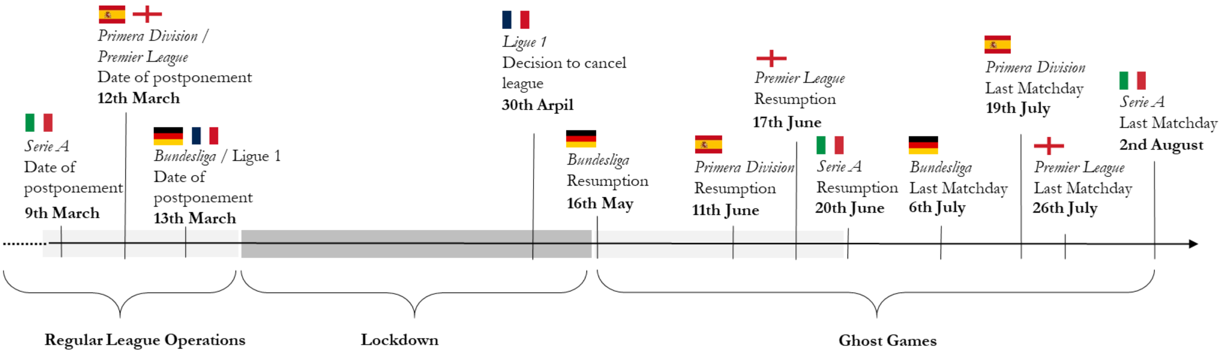
Following ghost games, the winning probabilities of home teams should be smaller in ghost games, while the winning probabilities of all away teams should increase. Indeed, during the 2019/2020 season, football teams of the top four European football leagues (Italy, Spain, Germany and England) that played in their home venue won 44% of all games before the lockdown but only won 41% of ghost games after resumption of the leagues' operations. We analyze to what extent the betting markets incorporate this change in the magnitude of the home advantage and thus may be perceived as efficient.

[3] See, for example, the following articles:
https://theconversation.com/as-football-returns-in-empty-stadiums-four-graphs-show-how-home-advantage-disappears-138685 (Singleton et al., 2020)
https://www.besoccer.com/new/covid-19-takes-away-home-advantage-836200 (BeSoccer, 2020)
https://www.dw.com/en/bundesliga-ghost-games-have-killed-home-advantage/a-53634123 (Da Silva, 2020)

We focus on the most prominent European leagues. Thus, our dataset features the first divisions of the following countries: England, Germany, Italy and Spain. We expect that the incentives of bookmakers to accurately price betting odds are largest for these leagues since they attract the most attention. We exclude France, as the French League 1 schedule was terminated without playing ghost games. To confirm that ghost games indeed altered the home advantage, we provide empirical evidence by means of a logistic regression (see table A1 in the appendix): In particular, at the start of resumption, the home advantage in ghost games is considerably reduced, which is consistent with previous findings (Fischer & Haucap, 2020).

Depending on the league, there were 9 to 12 match rounds to be played behind closed gates. The leagues resumed operations at different points in time. The German Bundesliga was the first league to restart, with ghost matches in mid-May. The Spanish Primera Division, the second top league to resume operations, joined almost one month later, with the English Premier League next and Italy's Serie A last. The timeline in figure 1 shows the developments in the top 5 European football leagues in 2019/2020:

FIGURE 1: TIMELINE



Notes: The figure displays the developments and decisions in the top 5 European football leagues with respect to the COVID-19 pandemic.

We collected data from www.football-data.co.uk, a website delivering comprehensive football statistics and betting odds from leagues around the world. The data include the odds of several bookmakers, such as Bet365, Betwin, Interwetten, Pinnacle, William Hill and VC Bet. The reciprocals of the bookmakers' odds represent the estimation of the probability of a win, defeat or draw. In a frictionless market, the probabilities should sum to 1. In practice, however, they rarely do so due to transaction costs and bookmakers' margins on all odds to cover the uncertainty of a game outcome, the so-called over-round (Bizzozero et al., 2016). To account for this, we derive the implicit probabilities for all possible game outcomes, i.e., a win of the home team (O_h), draw (O_d) or a win of the away team (O_a) (Deutscher et al., 2018).[4] We refer to these implicit probabilities as book probability. We calculate average book probabilities (*BookProb*) across the six betting companies.[5] In table 1, summary statistics of the variables as well as additional game-level information about the wins overall, before and during the ghost games are displayed.

TABLE 1: DESCRIPTIVE STATISTICS

	N	Mean	Q1	Median	Q3	SD
Variables utilized in regression (Home and away perspectives)						
Outcome	2'892	0.379	0.000	0.000	1.000	0.485
BookProb	2'892	0.378	0.231	0.356	0.505	0.191
Time	2'892	-109.1	-201.0	-131.0	-27.0	110.9
GhostGame	2'892	0.282	0.000	0.000	1.000	0.450
Home	2'892	0.500	0.000	0.500	1.000	0.500
Additional information (Game-level perspective)						
Home Team Win Post-Lockdown	408	0.414				
Home Team Win Pre-Lockdown	1'038	0.441				
Home Team Win Overall	1'446	0.434				
Away Team Win Post-Lockdown	408	0.350				
Away Team Win Pre-Lockdown	1'038	0.314				
Away Team Win Overall	1'446	0.324				
Draw Post-Lockdown	408	0.235				
Draw Pre-Lockdown	1'038	0.245				
Draw Overall	1'446	0.242				

Notes: This table reports descriptive statistics for variables employed as well additional information at the game level.

For the main analysis of this paper, we test the market efficiency of betting markets by means of regression methods to examine whether the implied winning probabilities of the home and away team alone are sufficient to predict the match outcome. Thus, we regress *BookProb* of a home team win, respective away team win, and additional covariates on the outcome of the bet, i.e., if the team under observation actually won – then the bet is won (= 1) and zero otherwise. If betting markets are efficient and incorporate new information correctly, implied bookmaker probabilities alone are sufficient to predict the match outcome (Bizzozero et al., 2018). Under this scenario, we would expect the covariates to be close to zero. By contrast, if the beta coefficients of the covariates are significantly different from zero, we would conclude that betting markets are inefficient. Thus, small p-values of the covariates provide statistical evidence that

[4] The probability of a home team win is derived as follows: $\hat{p}_h = \frac{1/O_h}{1/O_h + 1/O_d + 1/O_a}$ (1)

[5] The betting companies include Bet365, Betwin, Interwetten, Pinnacle, William Hill and VC Bet.

implied probabilities do not accurately reflect the conditional probability of the match outcome (Choi & Hui, 2014).

To capture a home bias, we include a variable *Home*, indicating whether the team plays home or away. We further include a variable *GhostGame*, indicating the time after leagues resumed operations: The variable equals 1 for all games played after the 15th of May 2020. We include an interaction term *Home × GhostGame*. If markets digest all relevant information immediately, the covariates should not yield any explanatory power. Thus, we are interested in β_4, which indicates market inefficiency during COVID-19-induced ghost matches. As our response variable is binary, equaling 1 for a win and 0 for a defeat, we estimate the following logit model:

$$Y_{i,m} = \beta_0 + \beta_1 BookProb_{i,m} + \beta_2 Home_{i,m} + \beta_3 GhostGame_m + \beta_4 Home_i \times GhostGame_m \tag{2}$$

$$f(\pi) = log\left(\frac{\pi_{i,m}}{1-\pi_{i,m}}\right) = Y_{i,m} \tag{3}$$

where i denotes the home or away team and m denotes the specific match. The probability π is combined with the linear predictor Y through the logit link function (Deutscher et al., 2018). We follow the established literature (e.g., Deutscher et al., 2018; Forrest & Simmons, 2008) by looking at the matches from the perspective of both the home and the away team. Thus, for every match, we have two observations, betting odds on the win of the home team and betting odds on the win of the away team.[6] We cluster standard errors at the match level to account for pairwise correlation.

In the next step, we include a variable *Time*, indicating the number of days to and from the first resumption day to account for whether market inefficiency persists over time or diminishes.[7] Thus, we interact *Home*, *GhostGame* and *Time,* which changes equation (2) to the following form:

[6] We also check a random assignment of games to either home or away and find that estimates remain robust.
[7] Bundesliga resumed operations on the 16th of May. Thus, we calculate *Time* as the difference between the match date and the 15th of May. Thus, *Time* takes on a positive value for all matches after the 16th of May and a negative value for all games prior to this date.

$$Y_{i,m} = \beta_0 + \beta_1 Odds_{i,m} + \beta_2 Home_{i,m} + \beta_3 GhostGame_m + \beta_4 Time_m + \beta_5 Home_i \times Time_m + \beta_6 GhostGame_m \times Time_m + \beta_7 Home_i \times GhostGame_m + \beta_8 Home_i \times GhostGame_m \times Time_m \quad (4)$$

We are interested in the coefficient β_7, which indicates the average effect of a home bias during the ghost matches, and in the coefficient β_8, which indicates whether any such bias increases or decreases over time.

5. RESULTS

For the main analysis, we estimate equation (2) from section 4. Table 2 shows the baseline estimations of market efficiency during the COVID-19 crisis. We estimate equation (2) with different samples that vary with respect to the time period employed. All samples include games from 2019/2020 until the lockdown in early 2020. We define eight time periods starting from 10 days after the resumption date in the Bundesliga (16th of May) and gradually increase it by 10 days until the last ghost game played in European top football (2nd of August).

The results from Table 2 suggest that, on average, there is no home field bias prior to the lockdown, i.e., in Table 2, it is priced into the odds as suggested by the coefficient of *Home*, which is not statistically significant. As expected, the average book probabilities are a highly significant predictor of match outcome. However, the estimates also show a home field bias during the beginning of the COVID-19-induced ghost matches, which is indicated by the significantly negative interaction term of *Home × GhostGame*. Statistical significance is present for the sample period until approximately the 15th of June. The book probability is significantly overestimated for the home team during ghost matches, as suggested by the negative coefficient of the interaction term. Thus, the implicit winning probability of the home (away) team as predicted by the bookmakers is higher (lower) than the actual occurrence of a win. This result suggests that new market information is not immediately priced into betting odds: Bookmakers do not accurately predict the COVID-19-induced ghost games and their impact on the home and away teams' winning probabilities. The results remain virtually the same when we change the estimation model (OLS, Probit) or when we employ the odds of the bookmakers Bet365, Betwin, Interwetten, Pinnacle, William Hill and VC Bet individually.[8]

TABLE 2: BASELINE ESTIMATION

Game Outcome

	I +10d. 26th May	II +20d. 5th June	III +30d. 15th June	IV +40d. 25th June	V +50d. 5th July	VI +60d. 15th July	VII +70d. 25th Aug.	VIII +78d. 2th Aug.
Constant	-2.245***	-2.249***	-2.260***	-2.305***	-2.331***	-2.340***	-2.333***	-2.346***
	[0.136]	[0.135]	[0.133]	[0.131]	[0.128]	[0.125]	[0.123]	[0.122]
BookProb	4.505***	4.516***	4.548***	4.682***	4.760***	4.785***	4.766***	4.803***
	[0.365]	[0.362]	[0.356]	[0.344]	[0.333]	[0.321]	[0.314]	[0.310]
Home	-0.0413	-0.0426	-0.0465	-0.0628	-0.0723	-0.0753	-0.073	-0.0775
	[0.132]	[0.132]	[0.132]	[0.132]	[0.132]	[0.131]	[0.131]	[0.131]
GhostGame	0.838*	0.646*	0.490*	0.142	0.158	0.0398	0.0107	0.0282
	[0.434]	[0.330]	[0.260]	[0.187]	[0.157]	[0.144]	[0.135]	[0.131]
Home x GhostGame	-2.444***	-1.533**	-1.465***	-0.483	-0.282	-0.0861	-0.0249	-0.02
	[0.844]	[0.632]	[0.479]	[0.326]	[0.275]	[0.249]	[0.235]	[0.228]
Model	Logit	Logit	Logit	Logit	Logit	Logit	Logit	Logit
Observations	2120	2152	2210	2374	2546	2698	2820	2892
R-squared	0.11	0.11	0.12	0.12	0.12	0.12	0.12	0.12

Notes: Dependent variable is the outcome of the match from the perspective of the respective team (home or away), equaling 1 for a win and 0 otherwise. *, **, *** indicate statistical significance at the 10%, 5% and 1% significance level, respectively. SEs are reported in brackets and clustered at the match level. The underlying samples include observations from the season 2019/2020 until specified in I to VIII. *BookProb* denotes the average book probability across the six bookmakers adjusted for the overround.

The results in Table 2 also show that the inefficiency is largest during the first days after resumption, whereas it gradually decreases and vanishes towards the end. There findings suggest that market inefficiencies are temporal and that by the beginning of July, bookmaker odds fully reflect the impact of ghost games on home advantage.

To investigate the time trend more systematically, we estimate equation (4) including a time variable that captures the number of days from the first ghost match after resumption to the specific game. Again, we estimate the model utilizing the average book probability, but we also check the estimates using individual bookmakers. The results in table 3 indicate that the book probability is again a highly significant predictor of actual game outcome. As expected, both *GhostGame* and *Time* are not statistically significant. On average, there is no home field bias prior to the lockdown period, as indicated by *Home.* However, the interaction term of *Home x GhostMatch* is statistically significant at the 5% level, suggesting that bookmakers

[8] The results also remain virtually the same when we do not correct for the overround of bookmakers.

misprice the home advantage during ghost games. Bookmakers systematically overestimate the probability of winning when playing at home, as indicated by the negative coefficient of *Home x GhostMatch*. However, this effect vanishes over time, as shown by the positive and statistically significant coefficient of *Home x GhostMatch x Time*.

TABLE 3: PERSISTENCE OVER TIME

	Game Outcome
Constant	-2.431***
	[0.234]
BookProb	4.825***
	[0.311]
Home	0.0972
	[0.370]
GhostGame	0.529
	[0.363]
Time	-0.000458
	[0.00117]
GhostGame x Time	-0.00863
	[0.00620]
Home x Time	0.00104
	[0.00203]
Home x GhostGame	-1.440**
	[0.627]
Home x GhostGame xTime	0.0254**
	[0.0106]
Model	Logit
Observations	2892
R-squared	0.13

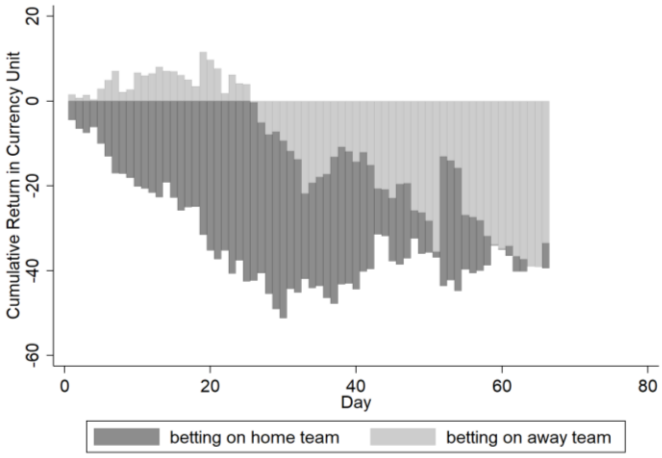
Notes: Dependent variable is the outcome of the match from the perspective of the respective team (home or away), equaling 1 for a win and 0 otherwise. *, **, *** indicate statistical significance at the 10%, 5% and 1% significance level, respectively. SEs are reported in brackets and clustered at the match level. *BookProb* denotes the average book probability across the six bookmakers adjusted for the overround.

The results from our analysis suggest that bookmakers overestimate the winning probability of home teams during ghost games. Thus, we exploit whether betting on away teams yields a better return than betting on home teams and whether these returns are positive. We analyze wagering an equal 1 currency unit per bet posted by the bookmaker Bet365 during the COVID-19-induced ghost games.[9] To this end, we calculate the cumulative payoff since resumption of league operations in the Bundesliga (16th of May 2020). The results are displayed in figure 1. The y-axis corresponds to the net payoff in the currency unit when wagering 1 currency unit per game.

[9] We also check the results using the odds from the other five bookmakers and find virtually no difference.

The results suggest that betting on away teams during ghost games is profitable at the beginning but becomes negative after match day 26 (20th June 2020). Betting on away teams remains negative until the end of the season and gradually converges with the cumulative return from betting on home teams. Betting on home teams yields a cumulative negative return from the resumption date of the Bundesliga onwards. Thus, betting on away teams not only yields a better return than betting at random, the expected return of which is negative due to the overround of bookmakers, it also yields a positive profit – at least for the early period of ghost games. This finding implies that betting markets are not semistrong-form efficient since it should not be possible to achieve above-average returns (Vaughan Williams, 2005). Utilizing the notion of market efficiency in betting markets by Thaler and Ziemba (1988), our evidence even suggests a violation of the weak market efficiency criterion, as the (temporal) return of betting on away teams is positive and significantly different from the return of betting on home teams.[10,11]

FIGURE 2: RETURN WHEN BETTING ON AWAY AND HOME TEAMS



Notes: The figure displays the absolute cumulative return when wagering an equal 1 currency unit per bet.

[10] The weak market condition by Thaler and Ziemba (1988) proposes that no bet should have a positive expected value. The strong market condition proposes that all bets should have expected values equal to (1 – t) times the amount bet.

[11] Utilizing an unpaired t-test, the difference of the return of betting on the home team and away team for the first month after resumption is statistically different from zero and significant at the 1%-level.

6. CONCLUSION

Our study sheds light on the processing of new public information in sports betting markets. We utilized the natural experiment of football games behind closed doors to assess whether betting markets are efficient in semistrong form. The news of ghost games was a clean signal of new public information: Playing in empty stadia will significantly alter the home field advantage, as crowd support is a key determinant thereof. Hence, an efficient betting market would require that bookmakers fully and immediately reflect the arrival of this information in their betting odds. We use betting odds from major bookmakers and 1,446 games in the top 4 European football leagues, including 408 ghost games. We find robust evidence that betting markets are inefficient, at least in semistrong form: Bookmakers systematically overestimate (underestimate) the home (away) team's winning probability during the early stage of the postresumption period, suggesting that the new information of a reduced home advantage in ghost games is not fully incorporated in the betting odds. After approximately 30 days, this market inefficiency vanishes.

Our evidence is linked to previous evidence regarding temporal inefficiencies (Deutscher et al., 2018). The same applies in the context of ghost games and their impact on home field advantage. However, it remains unclear whether bookmakers update their predictions once they gain sufficient evidence of an altered home advantage or whether the effect of ghost games on home advantage decreases over time as players might adapt and get used to the "new normal" (Fischer & Haucap, 2020). We leave this important subject for further research.

Similar to Choi and Hui (2014), our inferences are only generalizable to financial markets insofar as the behavior of bettors is comparable to investors in traditional financial markets. However, the implications for sports betting markets are more straightforward: The fact that these markets are weak-form efficient at most indicates that they provide ample opportunities for bettors to earn abnormal returns by quickly reacting to surprise announcements and disclosures.

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APPENDIX

TABLE A1: IMPACT OF GHOST GAMES ON THE HOME ADVANTAGE

Game Outcome

	I +10d. 26th May	II +20d. 5th June	III +30d. 15th June	IV +40d. 25th June	V +50d. 5th July	VI +60d. 15th July	VII +70d. 25th Aug.	VIII +78d. 2th Aug.
Constant	-0.781***	-0.781***	-0.781***	-0.781***	-0.781***	-0.781***	-0.781***	-0.781***
	[0.0669]	[0.0669]	[0.0669]	[0.0669]	[0.0669]	[0.0669]	[0.0669]	[0.0669]
Home	0.545***	0.545***	0.545***	0.545***	0.545***	0.545***	0.545***	0.545***
	[0.116]	[0.116]	[0.116]	[0.116]	[0.116]	[0.116]	[0.116]	[0.116]
GhostGame	0.964**	0.781**	0.632**	0.245	0.250*	0.164	0.136	0.164
	[0.434]	[0.331]	[0.254]	[0.183]	[0.151]	[0.136]	[0.128]	[0.123]
Home x Ghost	-2.573***	-1.715***	-1.639***	-0.633*	-0.455*	-0.312	-0.259	-0.275
Game	[0.903]	[0.634]	[0.481]	[0.323]	[0.268]	[0.240]	[0.224]	[0.217]
Model	Logit	Logit	Logit	Logit	Logit	Logit	Logit	Logit
Observations	2120	2152	2210	2374	2546	2698	2820	2892
R-squared	0.02	0.01	0.02	0.01	0.01	0.01	0.01	0.01

Notes: We estimate the following logistic regression: $Win_{i,m} = \beta_0 + \beta_1 Home_{i,m} + \beta_2 GhostGame_m + \beta_3 Home_i \times GhostGame_m$

Dependent variable is the outcome of the match from the perspective of the respective team (home or away), equaling 1 for a win and 0 otherwise. *, **, *** indicate statistical significance at the 10%, 5% and 1% significance level, respectively. SEs are reported in parentheses and clustered at the match level.

The underlying samples include observations from the season 2019/2020 until specified in columns I to VIII.