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The Importance of Betting Early

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Abstract

We analyze more than 1,250,000 bets on Italian soccer league matches. Our findings show that bettors do not improve their performance as the season progresses. We obtain evidence that early bettors, who place bets the days before the match, performed better then late bettors, who place bets on the same day of the event. We attribute this outcome to the increase of noisy information released the last day impairing late bettors' capacity to use very simple prediction methods, such as team rankings or last match result.

JEL-Code: D83, L83, D81

Keywords: sport forecasting, information overload, betting, prediction methods

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1. Introduction

This paper analyzes a large dataset of bets on Italian soccer league matches to investigate bettors' performance. The motivation for our study is twofold. The first is to investigate if non-professional bettors exhibit learning as time passes. To examine this issue, we analyze the winning percentages of bets placed in two different seasons of the Italian *Serie A* (that is, the Italian Major League). The second motivation originates from the hypothesis that bettors are unable to efficiently process all the available information. We investigate this assumption to check if bettors' performance depends on some specific pattern of information collecting. Betting on soccer relies on the availability of objective information, such as team rankings and win-loss records, which represent reasonably good predictors of match outcomes. Our dataset concerns non-experts betting small amounts of money on multiple events to increase their potential profits and only win the bet if all the events happen. For this reason, we believe that evidence can be significant to understand which factors are relevant in determining how they process and make use of the available information.

The paper is organized as follows. Section 2 presents a review of the relevant literature and discusses the relations with our approach. This is followed in Section 3 by the description of our hypotheses, dataset and econometric framework. Results are presented and discussed in Section 4. Section 5 summarizes and concludes.

2. Related literature

Since the 1970s, sport forecasting has been the object of extensive research focused mainly on two purposes: to ascertain if betting markets are informationally efficient and enable learning processes, and to check if experts make more accurate predictions than non-experts. Both strands of the literature aim at analyzing the conditions under which the availability of comprehensive information and professional advice is fully discounted by market prices (i.e., betting odds) and rules out observable biases that could allow speculators to make higher-than-average returns.

A large body of empirical evidence supports the assumption that bettors' behavior does not conform to the rational decision model and is affected by a number of cognitive biases. First, bettors show a clear tendency to under bet favorites and over bet long-shots. Second, they exhibit cognitive biases such as confirmation, gambler's fallacy and overconfidence related to inaccurate information processing. Third, bettors adopt a series of heuristics whose suitability is context-dependent. Finally, they are not effective enough in discounting the effect of noisy and redundant information and in reducing the impact of information overload.

A major strand of research concerns horse-race betting, which is a naturally occurring asset market in which the transmission of information from informed traders to uninformed traders is not typically smooth. This betting market is efficient if it aggregates less-than-perfect information owned by all the individuals and disseminates it to all the bettors through the publicly available information that is given by track and bookmakers' odds and handicappers' picks.

The classical paper by Figlewski (1979) investigated odds and forecasts of a number of bookmakers and experts concluding that racetrack betting markets discount quite well the available information, although bettors exhibit different degrees of accuracy depending on whether they are on-track bettors or off-track bettors. Snyder (1978), Hausch et al. (1981), Asch et al. (1984) and Crafts (1985) provided clear evidence on the tendency to under bet favorites and to over bet long-shots relatively to their true probability of winning. This finding was pointed out in laboratory experiments by Preston and Baratta (1948) and Yaari (1965), who showed that subjects tend to systematically undervalue events characterized by high probability and to overvalue events with low probability. In the 1980s, the implications of these findings for market efficiency were discussed by a wide literature, surveyed by Thaler and Ziemba (1988), Sauer (1998) and Williams (1999), who concluded that: "The case for information efficiency in racetrack betting markets has thus not been disproved (although neither has it been proved), at least in the sense of an opportunity to earn systematic abnormal expected returns, except perhaps at the level of and in the sense of insiders acting upon monopolistically held private information" (Williams 1999, p. 26).

If the analyses of the impact of insider information on racetrack betting led Williams to cautious conclusions, the analyses of betting in other sports can usually assume that information on market features spreads more easily. Baseball, basketball, football, and soccer are sports in which the sources of insider information are less relevant than in racetrack. Pope and Peel (1989) analyzed the fixed odds offered by bookmakers and the forecasts made by professional tipsters on UK soccer league matches. They argued that betting market was efficient in preventing bettors to gain abnormal returns on the basis of public information, but odds do not fully reflect the available information. This finding was confirmed by Forrest and Simmons (2000), who consider newspaper tipsters offering professional advices on English and Scottish soccer matches. They concluded that tipsters show a clear inadequacy in discounting the information publicly available on the newspaper. Moreover, their performance in predicting matches is less successful than following the very simple strategy of betting on home wins.

That the condition of being experts is not necessarily associated with a high degree of prediction accuracy was extensively discussed by Camerer and Johnson (1991) for various domains (medical, financial, academic). Their conclusion is that experts' superiority in processing information is not strictly related to performance superiority, which is crucially affected by the matching of experts' cognitive abilities with "environmental demands" (Camerer and Johnson 1991, p. 213). Similar findings for sport forecasting were provided by Boulier and Stekler (1999, 2003) for football, basketball and tennis, by Glickman and Stern's (1998) statistical methods to assess teams' strength on the basis of simple objective parameters, and by Anderson et al. (2005), who showed that in soccer betting experts fail to predict better than non-experts. Significantly enough, experts exhibit overconfidence by overestimating the accuracy of their forecasts.

An interpretation of this finding can be traced back to the classical paper by Oskamp (1965), who argued that the extent of collected information cannot be directly related to predictive accuracy. While predictive ability reaches a ceiling once a limited amount of information has been collected, confidence in the ability to make accurate decisions continues to grow proportionally (Oskamp 1982, Davis et al. 1994). This induces overconfidence in decision-makers, who become even more convinced of their understanding of the case at hand independently on the quality of collected information. Further exposure to sources of information is consequently distorted by the confirmation bias, according to which once decision-makers devise a strong hypothesis, they will tend to misinterpret or even misread new information unfavorable to this hypothesis (Kahneman and Tversky 1973).

Einhorn and Hogarth (1975), Gigerenzer et al. (1999) Benartzi and Thaler (2001) Martignon and Hoffrage (2002) and Rieskamp and Otto (2006) argued that decision making can be better explained by models of heuristics rather than by the standard rational decision model. Quoting Goldstein and Gigerenzer (2009, p. 3), "Cognitive heuristics are strategies that humans and other animals use. We call them fast because they involve relatively little estimation and frugal because they ignore information. A heuristic is not either good or bad per se. Its performance is dictated by features of the information environment, such as low predictability, or high cue redundancy." Anderson et al. (2005) use the recognition heuristics to account for non-experts' performance in soccer betting. According to Newell and Shanks (2004), recognition heuristics is assumed to demand little time, information, and cognitive effort, and exploits the relationship between a criterion value (that is, success in home win) and its predictors (that is, team rank position).

Heuristics performs quite well in environments affected by noisy and redundant information such as sport forecasting. Noisy information is defined as an information structure in which not only can one signal indicates several states, but also several signals can occur in the same state (Bichler and Butler 2007, Crawford and Sobel 1982). In Dieckmann and Rieskamp (2007), redundant information is defined as information composed by pieces highly correlated with each other and supporting the same prediction (positive redundancy), or that contradict each other and suggest incompatible predictions (negative redundancy).

By referring again to Oskamp (1965), if bettors are provided with a very rich source of information without activating a costly search process, confidence increases in relation to the beliefs that they had before because they are able to find explanation for that. For example, Bettman et al. (1993) provided support for the notion that people also select strategies adaptively in response to information redundancy. They showed that participants choosing between gambles search only for a subset of the available information when they encounter a redundant environment with positively correlated attributes. Negatively correlated attributes, in contrast, give rise to search patterns consistent with compensatory strategies that integrate more information. This cognitive bias is known as the illusion of knowledge, according to which beyond a threshold, more information on the event to predict increases self-confidence more than accuracy (Barber and Odean 2002).

This condition of information overload characterizes media information on Italian soccer, which provides the ground for our empirical analysis. The amount of information to be processed is greatly increased by the variety of communication systems on TV, internet and newspapers. Furthermore, much of the information is not original and viewers process continuously information received from other sources but differently presented. This situation leads bettors to be overwhelmed by using too many sources too quickly and creates a condition of information overload. The introduction of online betting caused further increase in the availability of information, which is also diffuse by online betting sites.

To investigate these issues we analyzed more than 1,250,000 bets on Italian soccer matches. Our database, which will be described in the next section, includes small bets, generally evenly distributed across subjects. Thus, it can be assumed that individuals included in our dataset are non-expert bettors.

3. Hypotheses, econometric strategy and data

Based on the literature surveyed in the previous section and on the data at hand, we intend to test two behavioral hypotheses.

H1 (learning hypothesis): over time bettors improve their performance, as they get more acquainted with the environment and the relative strength of the teams.

H2 (information overflow): as soon as the event approaches, the amount of noisy information available to bettors increases therefore reducing their winning ability.

We use a unique (large) dataset of online bets provided by a provider specialized in this field.[1] The company is located in Southern Italy, but bets are made from all the country. Users have to register and then bet online through credit card payments. We collect all matches of the last 10 game weeks of the Italian Soccer Major League (*Serie A*) for the season 2004/2005 and the first 10 game weeks for the season 2005/2006. Our dataset includes 1,205,597 single bets made by 7,093 registered users. Single bets may also be part of multiple bets including more then one event and may concern several events (e.g., which team wins, draw, goals scored, goals scored in the first half, and so forth). Multiple bets allow increasing potential profits and they are won only if all the events happen at the same time.

In our analysis, we focus on the simplest events 1, X, 2, 12, 1X, and X2 (where “1” stands for home win, “X” stands for draw, and “2” stands for away win). These types of event account for 85% of all bets.[2] The probability that bettor *j* correctly forecasts event *i* at time (i.e., game week) *t* can be modeled as follows:

$$WIN_{ijt} = \gamma_j + \tau DIST_{ijt} + f(t) + \underline{X}'_{jt}\underline{\beta} + \underline{Z}'_{it}\underline{\alpha} + \varepsilon_{ijt} \qquad (1)$$

where γ_j are individual fixed effects (capturing all the time-invariant characteristics of bettor *j*, including his or her intrinsic level of sophistication), $\underline{X}_{jt}$ is a vector of time-variant attributes of bettor *j* (such as the amount of money bet at time *t*, or the number of other events linked to event *i* in a multiple bet), $\underline{Z}_{it}$ is a vector of time-variant attributes of event *i* (such as whether the home team or the favorite team won the match), $DIST_{ijt}$ measures the distance from the time bettor *j* bets on event *i* to the time event *i* takes place, $f(t)$ is a function of time (i.e., game week), and ε_{ijt} is an idiosyncratic error clustered at the event level.

To test H1 (learning hypothesis), we introduce three specification of $f(t)$: linear trend (t); quadratic trend (t plus t^2); time dummies (ϑ_t). To test H2 (information overflow), the coefficient of

[1] See www.microgame.it.

[2] Using all bets would not change the results. Details are available from the authors upon request.

interest is τ, and we expect to find $\tau > 0$. Each hypothesis is tested *ceteris paribus* (that is, controlling for the other). Moreover, the inclusion of individual fixed effects in our main specification accommodates for the (observable and unobservable) time-invariant characteristics correlated with the outcome and the two treatments of interest.[3]

Our outcome variable is WIN_{ijt}, a dummy variable equal to one if the bettor correctly forecasts the outcome of the event, and zero otherwise. The main explanatory variable is the distance from the event ($DIST_{ijt}$), and it is measured in two different ways. First, we use the variable *betting distance*, which measures the distance of the individual bet from the event date in days. Second, we use *betting early*, which is a dummy variable equal to zero if the bet is made before the day of the event, and to one if it is made in the previous days. The control function $f(t)$, meant to evaluate the learning hypothesis, is expressed in terms of the variable *gameweek*, which is the ordinal week of the championship in which the match takes place.

The time-variant attributes of each event include several variables (Z_{it}). The variable *main teams* is equal to one if the bet concerns at least one team among F.C. Internazionale, Juventus F.C., A.C. Milan, and A.S. Roma (the four leading teams in *Serie A* during our sample period), and zero otherwise. *Strong wins* is a dummy variable equal to one if the stronger team (measured by the relative ranking position in the league) wins, and zero otherwise. *Home wins* is a dummy variable equal to one if the home team wins, and zero otherwise. Among the time-variant attributes of each bettor (X_{jt}), we include several variables as well. A*mount user* is the amount (in Euros) spent in game week *t* of each championship from every bettor in one or more single bets. *Other events* captures the number of the other single bets associated with the observed single bet within a multiple bet. *Odds* measures the official evaluation that the betting company gives to each event.

Because of the so-called *Calciopoli* affair, the scandal that emerged in 2006 accusing Juventus F.C., and other major teams including Milan A.C., A.C.F. Fiorentina, S.S. Lazio, and Reggina of rigging games by selecting favorable referees in the season 2005/06, we include a dummy variable for that season, in order to capture the possible effect of this fraud on the ability of bettors to forecast results.[4]

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[3] From a behavioral point of view, it would have been also interesting to analyze the effect of overconfidence on betting. Unfortunately, it was computationally impossible to relate the bet in game week *t* with the earnings/losses of the previous weeks. Moreover, we constructed an interaction term *timing***amount user*, which was also meant to capture some overconfidence, but it was never statistically significant and therefore we excluded it from our baseline estimations.

[4] The name *Calciopoli* is a pun on *Tangentopoli* (rough English translation: *Bribesville*), a corruption-based scandal emerged in the early '90s in Italian politics. As a result of the affair, the Italia Soccer Association stripped the 2004/05 and 2005/06 championships to Juventus F.C., and relegated the team to the second division. A number of officers of

Table 1 – Descriptive statistics

	Mean	Median	S.D.	Min	Max
Win	0.4507	0	0.4975	0	1
Betting distance	0.4431	0	0.7783	0	5
Betting early	0.3174	0	0.4654	0	1
Other events	5.1511	5	2.0612	0	13
Amount user	211.0471	153	241.8342	3	6018
Main teams	0.3986	0	0.4896	0	1
Gameweek	15.2582	9	10.9626	1	34
Home wins	0.3942	0	0.4887	0	1
Strong wins	0.3663	0	0.4817	0	1
Odds	2.2162	1.9	1.0327	1.05	18
2004/05 season	0.5067	1	0.4999	0	1

Notes. The number of observations is 1,205,575 for all variables.

Table 1 reports the descriptive statistics of the above variables. In our data, 45% of single bets are successful. However, this does not mean that bettors have such a high winning rate, because single bets may be part of multiple bets (on average slightly more than 5 bets are made in each play, with considerable variability), and some of them may be wrong. Indeed, the winning rate in multiple bets is quite low, 5% on average. Most bettors place their play in the same day of the event, as early bettors (i.e., those who play in the previous days) are about 32%. The average amount per bettor is €211, again with a large standard deviation. It seems that bettors in our sample are non-experts who usually make small-amount bets, with some exceptions. Typically, bets are made quite close to the events, but the standard deviation is high. Almost 40% of bets are made on the main four teams.

4. Empirical findings

Tables 2, 3 and 4 report our basic specifications. In the first three columns we do not control for individual effects, whereas this is done in the last three columns. The latter represent our preferred specifications, but it is instructive to compare results with and without fixed effects. As discussed above, to control for possible learning we use three specifications: the game week of the championship, which enters linearly (linear parametric estimation, columns 1 and 4); the game week of the championship squared (quadratic parametric estimation, columns 2 and 5); and the full set of *gameweek* dummies (non-parametric estimation, columns 3 and 6). For simplicity, we always

teams and referees were fined and/or banned from soccer for some time. The other teams were deducted a number of points. For empirical evidence, see Boeri and Severgnini (2011).

estimate a linear probability model.[5] Accordingly, the reported coefficients are marginal effects expressed in percentage points.

Table 2 shows very similar results across all specifications. The coefficient of the independent variable of interest, *betting distance*, is significantly positive and very stable: the further away from the event date the bet is, the higher the probability of winning. On average, betting one day earlier increases the chance of winning by about 2 percentage point, that is, by about 1.8% with respect to the average probability. This provides evidence of possible information overflow (H2): as the event gets closer, the bettor receives more information that he or she is unable to master, therefore increasing the possibility of mistakes. As long as the season goes on, however, bettors worsen their performance, as highlighted by the significantly negative coefficients for the variable *gameweek* in both the linear and quadratic specifications (each elapsed game week translates into a -1.8% of placing a winning bet on average). This result shows a “negative” learning (in contrast with H1).

Consistently with the previous literature, we find very strong effects for both *home wins* and *strong wins* (on average equal to 40.8% and 60.9%, respectively).[6] The ability of winning is positively and significantly affected by the monetary amount that each player bets, meaning that there is higher effort as long as more money is involved, with a large effect on the dependent variable (37.4% on average for an increase the amount bet equal to its standard deviation). Betting for the main teams gives a higher probability of winning. Betting on more than one event (which we can interpret as “professionalization” of amateur bettors that become more and more involved in this activity) also increases the probability of winning, although by only 0.8%. Columns 2 and 5 include the variable *gameweek squared*.

[5] The large sample size produces very accurate estimates of the marginal effects, which turn out to be almost identical to those estimated by (more computationally intensive) non-linear models such Logit or Probit. Results from these alternative estimation methods are available from the authors upon request.

[6] In these cases, and for all dichotomous variables, the change in probability is the outcome of moving from zero to one in the variable of interest.

Table 2 - Baseline specifications: distance from the event date (*betting distance*)

	(1)	(2)	(3)	(4)	(5)	(6)
Betting distance	0.008***	0.008***	0.007***	0.008***	0.008***	0.008***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
Home wins	0.184***	0.184***	0.182***	0.184***	0.184***	0.182***
	[0.002]	[0.002]	[0.002]	[0.001]	[0.001]	[0.001]
Strong wins	0.283***	0.283***	0.298***	0.284***	0.284***	0.297***
	[0.002]	[0.002]	[0.002]	[0.001]	[0.001]	[0.001]
Gameweek	-0.004***	-0.007***		-0.004***	-0.007***	
	[0.000]	[0.000]		[0.000]	[0.000]	
Gameweek squared		0.000***			0.000***	
		[0.000]			[0.000]	
Other events	0.007***	0.008***	0.007***	0.007***	0.007***	0.007***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Amount user	0.008	0.010*	0.006	0.008***	0.010***	0.006**
	[0.005]	[0.005]	[0.003]	[0.002]	[0.002]	[0.002]
Main teams	0.049***	0.048***	0.047***	0.049***	0.048***	0.047***
	[0.002]	[0.002]	[0.002]	[0.001]	[0.001]	[0.001]
Odds	-0.096***	-0.096***	-0.095***	-0.096***	-0.096***	-0.095***
	[0.001]	[0.001]	[0.001]	[0.000]	[0.000]	[0.000]
2004/05 season	-0.013***	-0.030***		-0.014***	-0.031***	
	[0.004]	[0.005]		[0.003]	[0.003]	
Gameweek dummies	NO	NO	YES	NO	NO	YES
Individual fixed effects	NO	NO	NO	YES	YES	YES
No. observations	1,205,575	1,205,575	1,205,575	1,205,575	1,205,575	1,205,575
No. individuals	7,093	7,093	7,093	7,093	7,093	7,093

Notes. Dependent variable: probability of correctly forecasting the single event (included in either a single or multiple bet). Estimation method: linear probability model as in equation (1). P-values in brackets. Significance at the 5% level is represented by ** and at the 1% level by ***.

We do not report its value since it is extremely small (in the order of four decimals); therefore the linear specification is fairly good. The same applies to the following tables, when this variable is included. As we would also expect, higher *odds* are related with a lower probability of winning (on average by -46.0% for an increase of odds equal to its standard deviation).

In Table 3 the main regressor of interest is *betting early*. This variable is significantly positive, meaning that the probability of making the correct bet is higher when the bet is made in the days before the event. On average, the chance of winning increases by 1.3 percentage points (that is, by 2.9% with respect to the average probability of winning). All the other variables confirm their behavior from a qualitative and a quantitative point of view.

Table 3 – Baseline specifications: betting before the event date (*betting early)*

	(1)	(2)	(3)	(4)	(5)	(6)
Betting early	0.013***	0.013***	0.011***	0.013***	0.013***	0.011***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
Home wins	0.184***	0.184***	0.182***	0.184***	0.184***	0.182***
	[0.002]	[0.002]	[0.002]	[0.001]	[0.001]	[0.001]
Strong wins	0.283***	0.283***	0.298***	0.284***	0.284***	0.297***
	[0.002]	[0.002]	[0.002]	[0.001]	[0.001]	[0.001]
Gameweek	-0.004***	-0.007***		-0.004***	-0.007***	
	[0.000]	[0.000]		[0.000]	[0.000]	
Gameweek squared		0.000***			0.000***	
		[0.000]			[0.000]	
Other events	0.008***	0.008***	0.007***	0.007***	0.008***	0.007***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Amount user	0.008	0.010*	0.006*	0.008***	0.010***	0.006**
	[0.005]	[0.005]	[0.003]	[0.002]	[0.002]	[0.002]
Main teams	0.048***	0.048***	0.047***	0.049***	0.048***	0.047***
	[0.002]	[0.002]	[0.002]	[0.001]	[0.001]	[0.001]
Odds	-0.096***	-0.096***	-0.095***	-0.096***	-0.096***	-0.095***
	[0.001]	[0.001]	[0.001]	[0.000]	[0.000]	[0.000]
2004/05 season	-0.013***	-0.030***		-0.014***	-0.031***	
	[0.004]	[0.005]		[0.003]	[0.003]	
Gameweek dummies	NO	NO	YES	NO	NO	YES
Individual fixed effects	NO	NO	NO	YES	YES	YES
No. of observations	1,205,575	1,205,575	1,205,575	1,205,575	1,205,575	1,205,575
No. of individuals	7,093	7,093	7,093	7,093	7,093	7,093

Notes. Dependent variable: probability of correctly forecasting the single event (included in either a single or multiple bet). Estimation method: linear probability model as in equation (1). P-values in brackets. Significance at the 5% level is represented by ** and at the 1% level by ***.

Table 4 includes the variables *betting distance* and *betting distance squared* in a quadratic specification that provides further evidence on our hypothesis H2. Whereas the linear term is still significantly positive, the quadratic term is usually statistically insignificant, with the exception of columns 4 and 5 where it is significantly negative. Since these are our preferred specifications, we conclude that the positive effect of betting early is decreasing in days. Again, the average effect of one day is around 2%. All other variables confirm their behavior.

Table 4 – Alternative specifications: quadratic distance from the event date

	(1)	(2)	(3)	(4)	(5)	(6)
Betting distance	0.010***	0.009***	0.007***	0.010***	0.010***	0.007***
	[0.002]	[0.002]	[0.001]	[0.001]	[0.001]	[0.001]
Betting distance squared	-0.001	-0.001	0.000	-0.001**	-0.001*	0.000
	[0.001]	[0.001]	[0.001]	[0.000]	[0.000]	[0.000]
Home wins	0.184***	0.184***	0.182***	0.184***	0.184***	0.182***
	[0.002]	[0.002]	[0.002]	[0.001]	[0.001]	[0.001]
Strong wins	0.283***	0.283***	0.298***	0.284***	0.284***	0.297***
	[0.002]	[0.002]	[0.002]	[0.001]	[0.001]	[0.001]
Gameweek	-0.004***	-0.007***		-0.004***	-0.007***	
	[0.000]	[0.000]		[0.000]	[0.000]	
Gameweek squared		0.000***			0.000***	
		[0.000]			[0.000]	
Other events	0.007***	0.008***	0.007***	0.007***	0.007***	0.007***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Amount user	0.008	0.010*	0.006	0.008***	0.010***	0.006**
	[0.005]	[0.005]	[0.003]	[0.002]	[0.002]	[0.002]
Main teams	0.048***	0.048***	0.047***	0.049***	0.048***	0.047***
	[0.002]	[0.002]	[0.002]	[0.001]	[0.001]	[0.001]
Odds	-0.096***	-0.096***	-0.095***	-0.096***	-0.096***	-0.095***
	[0.001]	[0.001]	[0.001]	[0.000]	[0.000]	[0.000]
2004/05 season	-0.013***	-0.030***		-0.014***	-0.031***	
	[0.004]	[0.005]		[0.003]	[0.003]	
Gameweek dummies	NO	NO	YES	NO	NO	YES
Individual fixed effects	NO	NO	NO	YES	YES	YES
No. of observations	1,205,575	1,205,575	1,205,575	1,205,575	1,205,575	1,205,575
No. of individuals	7,093	7,093	7,093	7,093	7,093	7,093

Notes. Dependent variable: probability of correctly forecasting the single event (included in either a single or multiple bet). Estimation method: linear probability model as in equation (1), with the addition of the regressor *betting distance squared*. P-values in brackets. Significance at the 5% level is represented by ** and at the 1% level by ***.

The last three tables address some heterogeneity issues, that is, they assess whether the timing effect is stronger in some specific subsamples. This is meant to further evaluate our information-overflow interpretation of the “betting early” effect we identify in our data.

In Table 5 we distinguish between bets on one of the main teams and on all the other teams, whilst in Table 6 we discriminate between bets done on many events (i.e., above the median of events in multiple bets) or lesser events. Finally, Table 7 distinguishes between “hard bets,” that is, bets whose amount is above the median value (here, we consider the amount of each multiple bet linked to every individual bet, which represents the unit of observation in our dataset). In the last row of each table we report the p-value of the Wald-test on the equality of the estimated coefficients for *betting distance* between the two subsamples. The subsample coefficients are statistically different between each other only in the case of “many events” and in some of the estimates of “main teams”.

In particular, in Table 5 *betting distance* is always significantly positive, but the size of its coefficient is about three times larger when only the main teams are involved in the bet. This is consistent with our interpretation of the disclosed “betting early” effect, because information overflow on the event date is even more relevant for major teams. Another difference concerns the variable *other events*, which is much bigger when the main teams are excluded. Compared with the previous estimations another relevant variable changes its behavior: *gameweek* is usually positive in the linear specification when the main teams are included, and negative otherwise. Therefore, we observe some learning in this specification.

In Table 6, interestingly, the “betting early” effect is quantitatively larger for bets linked to other bets in a multiple play. Again, in these circumstances, information overflow is likely to exacerbate fallacies in decision making and to reduce the probability of winning. In Table 7, instead, we do not detect statistically significant differences in the size of coefficients for “hard bets” versus the others. Interestingly, the amount of registered users that place the 50% of bets that we code as “hard” are considerably less (1,352) than the users that place the other 50% of bets (7,014). This means that only a small fraction of sophisticated bettors place higher-than-median bets, but their behavior in terms of informational patterns is not significantly different from the behavior of the other, less sophisticated, bettors.

Table 5 – Heterogeneity results: main teams vs. other teams

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Main teams		Main teams		Main teams		Main teams		Main teams		Main teams	
	YES	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES	NO
Betting distance	0.013***	0.004***	0.013***	0.003***	0.011***	0.005***	0.013***	0.003***	0.013***	0.003***	0.012***	0.004***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
Home wins	0.115***	0.244***	0.115***	0.244***	0.124***	0.240***	0.115***	0.244***	0.115***	0.244***	0.124***	0.240***
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.003]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
Strong wins	0.479***	0.099***	0.481***	0.098***	0.485***	0.091***	0.479***	0.099***	0.481***	0.098***	0.486***	0.091***
	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.002]
Gameweek	0.004***	-0.007***	-0.003***	-0.012***			0.004***	-0.007***	-0.003***	-0.012***		
	[0.000]	[0.000]	[0.001]	[0.001]			[0.000]	[0.000]	[0.000]	[0.000]		
Gameweek squared			0.000***	0.000***					0.000***	0.000***		
			[0.000]	[0.000]					[0.000]	[0.000]		
Other events	0.002***	0.012***	0.002***	0.012***	0.002***	0.012***	0.002***	0.012***	0.002***	0.012***	0.002***	0.011***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Amount user	0.000	0.009	0.005	0.012**	0.002	0.006	0	0.009***	0.005	0.013***	0.003	0.006*
	[0.007]	[0.006]	[0.007]	[0.006]	[0.005]	[0.004]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]
Odds	0.201***	-0.149***	0.162***	-0.170***			0.204***	-0.151***	0.162***	-0.171***		
	[0.005]	[0.005]	[0.007]	[0.006]			[0.004]	[0.004]	[0.005]	[0.004]		
Gameweek dummies	NO	NO	NO	NO	YES	YES	NO	NO	NO	NO	YES	YES
Individual fixed effects	NO	NO	NO	NO	NO	NO	YES	YES	YES	YES	YES	YES
No. of observations	480,534	725,041	480,534	725,041	480,534	725,041	480,534	725,041	480,534	725,041	480,534	725,041
No. of individuals	6,814	6,905	6,814	6,905	6,814	6,905	6,814	6,905	6,814	6,905	6,814	6,905
Wald test p-value	0.467		0.074		0.007***		0.231		0.007***		0.001***	

Notes. Dependent variable: probability of correctly forecasting the single event (included in either a single or multiple bet). Estimation method: linear probability model as in equation (1) in separate subsamples (events involving main teams vs. events involving other teams). P-values in brackets. The Wald test p-value captures the significance of the difference of the coefficients of *betting distance* in the two subsamples. Significance at the 5% level is represented by ** and at the 1% level by ***.

Table 6 – Heterogeneity results: bets with many events vs. others

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Many events		Many events		Many events		Many events		Many events		Many events	
	YES	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES	NO
Betting distance	0.011***	0.005***	0.011***	0.005***	0.011***	0.004***	0.011***	0.005***	0.011***	0.005***	0.011***	0.004***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
Home wins	0.251***	0.088***	0.251***	0.088***	0.247***	0.089***	0.251***	0.088***	0.251***	0.088***	0.247***	0.089***
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
Strong wins	0.345***	0.192***	0.345***	0.192***	0.360***	0.203***	0.345***	0.192***	0.346***	0.192***	0.359***	0.202***
	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.002]
Gameweek	-0.003***	-0.004***	-0.007***	-0.007***			-0.003***	-0.004***	-0.007***	-0.007***		
	[0.000]	[0.000]	[0.001]	[0.001]			[0.000]	[0.000]	[0.000]	[0.001]		
Gameweek squared			0.000***	0.000***					0.000***	0.000***		
			[0.000]	[0.000]					[0.000]	[0.000]		
Other events	0.009	0.001	0.012**	0.003	0.000	0.003	0.012***	0.000	0.015***	0.002	0.005*	0.002
	[0.006]	[0.006]	[0.006]	[0.006]	[0.003]	[0.004]	[0.003]	[0.004]	[0.003]	[0.004]	[0.003]	[0.004]
Amount user	0.032***	0.067***	0.031***	0.066***	0.031***	0.066***	0.034***	0.067***	0.033***	0.067***	0.032***	0.066***
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
Main teams	-0.113***	-0.088***	-0.114***	-0.088***	-0.113***	-0.088***	-0.112***	-0.088***	-0.112***	-0.088***	-0.110***	-0.088***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
Odds	-0.011**	-0.036***	-0.009*	-0.054***			-0.009**	-0.037***	-0.011***	-0.055***		
	[0.005]	[0.005]	[0.005]	[0.006]			[0.004]	[0.005]	[0.004]	[0.005]		
Gameweek dummies	NO	NO	NO	NO	YES	YES	NO	NO	NO	NO	YES	YES
Individual fixed effects	NO	NO	NO	NO	NO	NO	YES	YES	YES	YES	YES	YES
Observations	691,104	514,471	691,104	514,471	691,104	514,471	691,104	514,471	691,104	514,471	691,104	514,471
Individuals	6,119	6,243	6,119	6,243	6,119	6,243	6,119	6,243	6,119	6,243	6,119	6,243
Wald test p-value	0.000***		0.000***		0.000***		0.000***		0.000***		0.000***	

Notes. Dependent variable: probability of correctly forecasting the single event (included in either a single or multiple bet). Estimation method: linear probability model as in equation (1) in separate subsamples (bets linked to a higher-than-median number of multiple bets vs. others). P-values in brackets. The Wald test p-value captures the significance of the difference of the coefficients of *betting distance* in the two subsamples. Significance at the 5% level is represented by ** and at the 1% level by ***.

Table 7 – Heterogeneity results: bets involving larger-than-median amounts vs. others

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Hard bets		Hard bets		Hard bets		Hard bets		Hard bets		Hard bets	
	YES	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES	NO
Betting distance	0.008***	0.008***	0.008***	0.008***	0.007***	0.008***	0.008***	0.008***	0.008***	0.008***	0.007***	0.009***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
Home wins	0.184***	0.184***	0.184***	0.184***	0.182***	0.182***	0.184***	0.184***	0.184***	0.184***	0.182***	0.183***
	[0.003]	[0.002]	[0.003]	[0.002]	[0.003]	[0.002]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
Strong wins	0.295***	0.274***	0.295***	0.274***	0.311***	0.284***	0.295***	0.274***	0.295***	0.274***	0.311***	0.284***
	[0.004]	[0.003]	[0.004]	[0.003]	[0.004]	[0.003]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
Gameweek	-0.003***	-0.004***	-0.008***	-0.007***			-0.003***	-0.005***	-0.008***	-0.007***		
	[0.000]	[0.000]	[0.001]	[0.001]			[0.000]	[0.000]	[0.000]	[0.000]		
Gameweek squared			0.000***	0.000***					0.000***	0.000***		
			[0.000]	[0.000]					[0.000]	[0.000]		
Other events	0.007***	0.008***	0.007***	0.008***	0.007***	0.008***	0.006***	0.008***	0.007***	0.008***	0.007***	0.008***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Amount user	0.043***	0.054***	0.042***	0.053***	0.041***	0.053***	0.043***	0.055***	0.042***	0.054***	0.041***	0.053***
	[0.003]	[0.002]	[0.003]	[0.002]	[0.003]	[0.002]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
Main teams	-0.094***	-0.097***	-0.094***	-0.097***	-0.094***	-0.097***	-0.094***	-0.097***	-0.094***	-0.097***	-0.094***	-0.096***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
Odds	0.008	-0.032***	-0.018**	-0.045***			0.007*	-0.039***	-0.020***	-0.051***		
	[0.008]	[0.005]	[0.008]	[0.006]			[0.004]	[0.004]	[0.005]	[0.005]		
Gameweek dummies	NO	NO	NO	NO	YES	YES	NO	NO	NO	NO	YES	YES
Individual fixed effects	NO	NO	NO	NO	NO	NO	YES	YES	YES	YES	YES	YES
No. of observations	596,037	609,538	596,037	609,538	596,037	609,538	596,037	609,538	596,037	609,538	596,037	609,538
No. of individuals	1,352	7,014	1,352	7,014	1,352	7,014	1,352	7,014	1,352	7,014	1,352	7,014
Wald test p-value	0.936		0.991		0.366		0.464		0.405		0.679	

Notes. Dependent variable: probability of correctly forecasting the single event (included in either a single or multiple bet). Estimation method: linear probability model as in equation (1) in separate subsamples (bets involving a higher-than-median amount of the multiple bet vs. others). P-values in brackets. The Wald test p-value captures the significance of the difference of the coefficients of *betting distance* in the two subsamples. Significance at the 5% level is represented by ** and at the 1% level by ***.

5. Conclusion

We have analyzed more than 1,250,000 bets on Italian soccer matches to test if bettors improve their winning percentage with respect to the timing of each bet. We do not find evidence of improvement in bettors' performance attributable to learning. Even more, their performance gets worse as the season moves forward. More interestingly, we find that betting timing matters. We obtain a small but statistically significant difference in the winning probability of early bettors versus late bettors. The poorer forecasting performance of later bettors is attributed to an inefficient processing of information, also consistent with the heterogeneity results that we are able to disclose thanks to the richness of the data.

The late bettors' decision process is affected by various cues that, unknown to the earlier bettors, have scarce relevance for predicting the outcomes. The excess of noisy information (especially harsh if the same individual decides to bet on the main teams or on multiple events) reduces the possibility of using very simple prediction methods, such as team rankings or home team winning. Moreover, the use of these criteria and cues greatly improves the possibility of placing a winning bet. Our findings support the hypothesis that forecasting activity is negatively affected when the number of cues is too large in comparison with information processing capacity, and provide an explanation to the fact that in betting simple prediction rules usually perform better than models based on extensive knowledge.

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