



# Everyone's a winner: The market impact of technologically advantaged agents



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## HIGHLIGHTS

- There is a consistent transfer of wealth from early to late bettors.
- The utility of early bettors is improved by the late bettors' price impact.
- Investor utility should be considered before regulatory intervention.

## ARTICLE INFO

### Article history:

Received 13 March 2017

Received in revised form

18 April 2017

Accepted 21 April 2017

Available online 26 April 2017

### JEL classification:

C92

D80

D84

### Keywords:

Market making

Market regulation

Heterogeneous agent utility

## ABSTRACT

Using betting data, we show that a market with agents having heterogeneous utility can include a net transfer of wealth to technologically advantaged agents (TAAs) from non-TAAs with the transaction proving beneficial to both in terms of their realized utility.

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## 1. Introduction

We show that the consistent transfer of trading returns from one agent to another does not necessarily imply an inequitable or unfair market, even when the beneficiary agent is exploiting a technological advantage to make profit.

There is an ongoing debate around high frequency trading practices in financial markets, as some of these practices are seen as predatory. Agents with faster access to bid/offer prices, through faster hardware connectivity and/or co-location on an exchange, may be deemed to have an unfair advantage. Regulatory bodies in different countries have responded in a variety of ways to the challenges posed by technologically advantaged agents (TAAs), with some considering transaction taxes and restrictions

on order cancellations or algorithm usage (see [Linton et al., 2013](#); [O'Hara, 2015](#)). On the other hand, [Menkveld \(2013\)](#) provides direct evidence of how the entrance of TAAs can be beneficial (through reduced spreads).

We analyze a market where technology can afford TAAs a timing advantage in placing trades. We examine the actions of these TAAs in order to investigate whether their technological advantage results in an inequitable market. We achieve this by looking at the price impact of their actions on the non-TAA's utility. What we find is that rather than exploiting the non-TAAs, the TAAs are meeting a demand for payoffs in the most popular payoff states, resulting in an improved realized utility score for the non-TAAs.

The tote betting market provides the opportunity to separate investors with different utility functions. The conventional wisdom is that informed bettors bet late (see e.g. [Asch et al., 1982](#)) and we present strong evidence to support this. Late bettors gain two main advantages: firstly, they obtain the most accurate estimate of the final odds, secondly, they hide their own probability estimates which might otherwise be revealed through their bets. The tote publishes prices based on updated pool totals at a frequency of

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1 or 2 updates per minute. The penultimate tote cycle is the last set of odds displayed after which valid bets can be placed. A level of sophistication in bet timing and transmission is required to guarantee bet placement after this cycle but before the pools close.

The discussion on market regulation issues in betting markets to date has focused on the use of insider information rather than TAAs (see Peirson, 2011). Using time-stamped betting amounts on each horse, we separate the tote pool into those amounts bet before and after the penultimate tote cycle (the ‘early’ and ‘late’ betting periods). This allows us to separate the amount bet by the TAAs and the non-TAAs and to examine the utility functions implied by the distributions of these agents’ bets associated with different odds.

## 2. Materials & methods

### 2.1. Data

The data set includes tote market win pool betting for each runner over 174,000 races and includes over 2.8 million price quotes for 1.4 million runners across 39 tracks in the USA and Canada from May 2011 to August 2016. It includes the amounts bet on each runner to produce the final odds and the last predicted set of odds published by the tote (the end of the penultimate tote cycle). The difference between the two amounts being largely due to the amount placed by TAAs.

Track-specific takeout rates (i.e. the percentage of the betting pool deducted by the tote to cover operating costs and profit) are used to reconstruct the odds implied by the amounts bet. The tote also applies ‘breakage’, whereby odds implied by the amounts bet are rounded down to one decimal place before display, and bets are settled on this final figure.

The dividends, including breakage, are calculated as:

$$div_i = \left\lfloor \frac{10 * \sum_i \frac{wamt_i}{wamt_i} * (1 - takeout)}{10} \right\rfloor, \tag{1}$$

where  $\lfloor x \rfloor$  represents a rounding down ( $floor(x)$ ) function to implement tote breakage and  $wamt_i$  is the amount bet on horse  $i$ .

### 2.2. The favorite longshot bias

The favorite-longshot bias (FLB) is a phenomenon observed in betting markets whereby longer/shorter odds prices are over-/under-bet (relative to the probability of a payoff).<sup>1</sup> We use the FLB to test for evidence of risk-loving preferences among two distinct agents: TAAs and non-TAAs. To do this we report the coefficient from a conditional logistic regression (CL) (as per Bolton and Chapman, 1986) of the race outcome on the log of the odds.

The probability of runner  $i$  winning the race is given as:

$$p_i = \frac{\exp(\beta \log(div_i))}{\sum_i \exp(\beta \log(div_i))}. \tag{2}$$

The  $\beta$  value is obtained by maximizing a log-likelihood (LL) score,  $\mathcal{L}(\beta)$ :

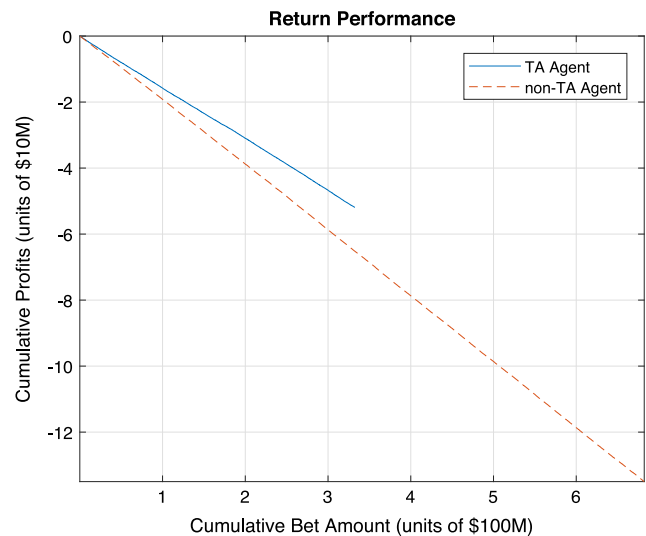
$$\exp(\mathcal{L}(\beta)) = \prod_m \frac{\exp(\beta \log(div_m)^w)}{\sum_i \exp(\beta \log(div_m)^i)}, \tag{3}$$

<sup>1</sup> See Ottaviani and Sørensen (2008) for a review of the main explanations for causes of the bias. Williams and Paton (1998) defined two separate bettor types to explain variation in the FLB and we also split the betting pool into two separate representative agents.

**Table 1**

The conditional logistic  $\log(div_i)$  parameter,  $\beta$ , and likelihood scores for the three sets of odds: early bettors (non-TAAs), late bettors (TAAs) and the final combined odds. The pool percentage breaks down the percentage of the total amount wagered into amounts up to and after the odds at the penultimate cycle are calculated. Test statistics for the  $\beta$  coefficients are given in square brackets, we can reject the null hypothesis of an unbiased coefficient,  $H_0 : \beta = -1.0$ , with p values <0.00001 in each case.\*\*The late bettor LL value is NA because the late bettors bet zero on some horses that win races, resulting in a likelihood score of zero. In this case they are completely avoiding betting on some horses as they represent bad value, rendering the difference in amounts from the penultimate to the final cycle an incomplete market.

	Early	Late	Final (Combined)
Ave. Pool Percentage	66.4%	33.6%	100%
CL Coefficient ( $\beta$ )	-1.152	-0.807	-1.111
	[-363.3]	[-342.9]	[-356.4]
Average Bet Return	-19.82%	-15.7%	-18.4%
LL score	-252,808	NA**	-246,207



**Fig. 1.** A comparison of the cumulative returns of the TAAs and non-TAAs.

where  $\log(div_m)^i$  is the log of the dividend for runner  $i$  in race  $m$  and  $\log(div_m)^w$  is the log of the dividend for the winning runner in race  $m$ , ( $-1 \leq m \leq 174,000$ ).

An unbiased coefficient is given by  $\beta = -1.0$ , values more negative/positive than this indicate the presence of the FLB/reverse FLB.

In our data set, of the \$1.18 billion bet in the win market, \$396 million was bet in the final tote cycle (i.e. TAAs bet 33.6% of the total market volume, see Fig. 1). The results of estimating (2) for odds determined by the early and late bettors separately and combined are given in Table 1. The final (combined) odds demonstrate a clear FLB ( $\beta = -1.11$ ), and this is more pronounced for the odds set by early bettors ( $\beta = -1.152$ ). The move toward an unbiased measure is coming from the TAAs whose bets are focused heavily on the favorites. The average bet return for all agents corresponds to the average track take plus breakage (-18.4%). The non-TAAs do worse than the track take by 1.4%, while the TAAs are recovering some of the take, losing only 15.7%. The higher LL score associated with the estimations based on the final (cf. early) odds suggest that the bets of TAAs improve the accuracy of the early odds (LLratio test score: 13,441,  $p < 0.0001$ ).

### 2.3. Implied utility functions

We use Weitzman’s (1965) method to imply two different representative agent utility functions for the TAAs and non-TAAs. We first separate the data into return bins based on the final

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