Misperception explains favorite-longshot bias: Evidence from the Finnish and Swedish harness horse race markets

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Abstract

We use a unique data set from Finnish and Swedish horse race betting markets to explain the favorite-longshot bias. The data set includes a complete set of odds for exotic markets. We use the exotic market odds in conjunction with the win market odds and find convincing support for the misperceptions explanation of the favorite-longshot bias rather than the risk-love explanation. Furthermore, our data provides evidence of a specific type of failure to reduce compound lotteries. Namely, it seems that bettors do not assess the exotic market events as simple lotteries but instead consider the race for the first place and the race for the second place in a sequential form.

Keywords: betting, favorite-longshot bias, misperception

JEL Classification: D03, D8

1. Introduction

The favorite-longshot bias, first documented by Griffith (1949), is probably the most well documented and longstanding anomaly in race track betting markets. The bias describes the pattern that longshots tend to attract more bets than justified by their probability of winning, whereas favorites attract too few bets. This translates to higher average returns to bets on favorites than bets on longshots. For example, Thaler and Ziemba (1988) found that bets on longshots returned less than 50% of the total money, whereas bets on extreme favorites were slightly profitable.

The literature on the favorite-longshot bias in the win market, where bets are simply made on the winner of the race, is voluminous including for example Weitzman (1965), Ali (1977) and Jullien and Salanie (2000). In an influential paper Snowberg and Wolfers (2010) argued that win market data alone cannot differentiate between competing explanations of the bias. They instead combined exotic market data with win market data, and used non-parametric methods to provide support for an explanation based on misperception of probabilities rather than risk-loving behavior. However, their results depend crucially on the assumption that bettors fail to reduce compound lotteries in a specific way when assessing exotic bet outcomes. This assumption was a necessity because their data include only the odds of the winning combinations in the exotic markets. Furthermore, as we show, the lack of data on non-winning combinations causes a selection bias in their data because non-winners are, on average, weaker runners than the winners.

The novelty of our paper comes from our data. We have a complete set of odds from both win and quinella markets for each race. In the quinella market, an example of an exotic market, bets are made on runners ranked first and second, in either order. Our aim is similar to Snowberg and Wolfers (2010) but we are able to utilize a complete set of exotic bet odds for each race. This allows us to provide more direct and convincing empirical support for the misperception explanation of the bias. In particular, we can directly observe that the specific form of a failure to reduce compound lotteries used by Snowberg and Wolfers seems realistic.

The paper proceeds as follows. In Section 2 we provide a literature review. Section 3 describes the data. In Section 4 we show that we can clearly reject the risk-love explanation for the favorite-longshot bias by noting that the magnitude of the bias differs considerably across the win and quinella markets. In Section 5 we present support for the misperception explanation paired with a failure to reduce compound lotteries. We then check the robustness of our results to separately examining Finnish and Swedish, as well as weekday and weekend races, in Section 6. Finally, Section 7 concludes.

2. Background

There are two main explanations for the favorite-longshot bias. The original explanation, given by Griffith (1949), is referred to as misperception of probabilities by bettors. That is people make systematic errors in assessing probabilities such that, on average, large probabilities are underestimated and small probabilities are overestimated. Therefore, a bet on a longshot is perceived by the bettor as a more favorable investment than it actually is. The theoretical foundation for this explanation is given by Prospect Theory (Kahneman and Tversky 1979). Much of the empirical support for the prospect theory has been gathered in experimental setups (see for example Barberis 2013). Therefore betting market studies provide an important real world complement to experimental studies.

Another way to explain the favorite-longshot bias, first proposed by Weitzman (1965), is to simply attribute the bias to rational, but risk-loving, behavior. A bet on a longshot is riskier than a bet on a favorite. Therefore, in equilibrium, risk-loving bettors end up depressing the average returns on longshots below the average returns on favorites. Note that according to this explanation the average rate of return should decrease with odds at a similar rate across the win and quinella market.

There are also additional, more detailed, explanations for the favorite-longshot bias. Many of these can be reduced to our two broad explanations, at least in terms of the implications for equilibrium odds.[1] For example, Ottaviani and Sorensen (2010) and Sobel and Raines (2003), have attributed the favorite-longshot bias to heterogeneity of information. From our point of view these explanations boil down to observed misperception of probabilities. Ottaviani and Sorensen (2008) provide a more detailed survey of proposed explanations with an emphasis on the information-based explanations.

Snowberg and Wolfers (2010) use a large-scale data set to differentiate between the misperception explanation and the risk-love explanation. They derive testable predictions about the pricing of exotic bets. According to their analysis, bettors' misperception of probabilities is a more precise explanation for the favorite-longshot bias. Their analysis, however, suffers from a sample selection problem, as they only have odds of winning combinations from exotic markets. Our analysis has an important advantage relative to Snowberg and Wolfers (2010) in that, due to inclusion of odds of non-winning combinations, our data can make a direct distinction between bettors failing or not to reduce

[1] Snowberg and Wolfers (2008) explicitly use this characterization.

compound lotteries in exotic markets. In this sense, our paper also complements the experimental literature on the assessment of compound lotteries (see Camerer and Ho 1994).

Jullien and Salanie (2000) and Gandhi (2007) attempted to use only win market data, together with specific functional form assumptions, to distinguish between explanations. Their results are mixed and they depend on how much modeled heterogeneity is allowed. In particular, Jullien and Salanie provide evidence that the cumulative prospect theory fits their data much better than expected utility theory whereas Gandhi, who allows bettor heterogeneity, ends up favoring the expected utility over the behavioral alternatives.

3. Data

We utilize daily live odds data from Finnish and Swedish harness horse racing from September 2012 to November 2014. This data includes exotic markets, that is markets beyond the simple win market. Both Finnish and Swedish horse race betting markets are organized as parimutuel pools that are run by a government-granted monopoly.[2] We use the win market and the quinella market closing odds in our analysis. The winning combination of the quinella market consists of runners ranked first and second, in either order. The quinella market is chosen as the only exotic market because it is available for all races.[3]

In parimutuel betting all money that is bet in a market is pooled, after which the operator collects the track take in our data between 15 and 20 percent of the total pool. The remaining money is then distributed to the bettors of the winning combination in proportion to their stakes. Therefore the fractional odds O_i, that is the potential net return of a bet on i, are:

$$1 + O_i = (1 - \tau)\frac{\sum_j v_j}{v_i}, \tag{1}$$

where τ denotes the track take, and v_i denotes the total amount of money bet on i. The formula is correct up to minimum odds and roundings. In our data the minimum odds is zero which means that bets on selections whose volume share is greater than $1 - \tau$ potentially yield zero rather than negative profit. Importantly, the pools of the quinella and win markets are completely separate. Therefore the odds of the markets do not directly depend on each other through the parimutuel mechanism.

[2] In both countries the monopolies face minor competition from internet betting sites that operate abroad.
[3] For example, trifecta betting does not take place in all races

In parimutuel betting the odds are therefore determined directly by the amounts of money bet on each combination. This is in contrast to fixed odds betting and betting exchanges where other factors may affect pricing as well. The simplicity of odds setting within parimutuel markets facilitates studying bettors behavior only through the final odds.

The data were collected programmatically from the *XML*-feed provided by the Finnish tote operator Fintoto. After discarding dead heats and races with abnormal track takes the final data consist of 20,210 races.

The novelty of our data is that we were able to record odds of all, rather than just winning, combinations in the exotic markets. This allows us to observe the magnitude of the favorite-longshot bias also in the quinella market. Snowberg and Wolfers (2010) use exotic market data in a largely similar fashion, however they only have data on winning combinations. Therefore, their analysis is limited to asking which of the potential explanations, risk-love or misperceptions, is better in explaining the exotic odds *only* for winning combinations. We are instead able to directly reject the risk-love explanation and observe just how far the misperceptions explanation fares in explaining the bias.

4. Rejection of the risk-love explanation

Figure 1 displays the favorite-longshot bias in the win and quinella markets separately. The figure is produced by Loess-smoothing (Cleveland et al., 1988) the average returns of bets.

[INSERT FIGURE 1 HERE]

The bias exists in both win and quinella market, but is considerably larger in the win market. The result is intuitive: bet with odds of for example 20/1 clearly represents a longshot in the win market but would typically be among the most favored selections in the quinella market.

The difference in average returns across the win and quinella markets in Figure 1 is fundamentally incompatible with the risk-love explanation of the favorite-longshot bias because under this explanation any bets with equal odds are equally risky and should therefore have the same expected return. An equilibrium requires that the utility of betting on any option must be the same. Normalizing the utility of losing a bet to zero and the utility of not betting to unity we obtain

$$pU(w_0 + bO) = 1, \tag{2}$$

where p is the probability of the bet winning, O is the fractional odds, that is the potential net return of the bet, and w_0 and b are the undetermined initial wealth and bet size. According to the risk-love explanation we could fit a suitable utility function to map each level of odds to the probability of winning within each market. However, the more pronounced the favorite-longshot bias is, the more risk-love the utility function should exhibit. In Figure 1, a single utility function is unable to simultaneously explain the average returns of both markets. In particular, explaining return in the win market requires considerably more risk-love. Our data therefore clearly rejects the risk-love explanation of the favorite-longshot bias.[4]

When assessing the plausibility of misperception of probabilities as an explanation of the favorite-longshot bias it is necessary to account for how the bettors assess the probability of compound bets. In the simplest case, bettors are able to reduce compound lotteries and simply assess the probability of pair $\{A, B\}$ coming in the first two places in either order as $\pi_{AB} = \pi(p_{AB})$, where π is a probability weighting function which maps the actual probability of an event to a subjective probability. In Section 5 we will consider an alternative possibility that the bettors fail to reduce compound lotteries and assess the probability of pair $\{A, B\}$ as

$$\pi_{AB} = \pi(p_A)\pi(p_{B|A}) + \pi(p_B)\pi(p_{A|B}), \tag{3}$$

where p_A denotes the actual probability of horse A to win the race and $p_{B|A}$ denotes the actual probability of horse B to place second conditional on horse A winning the race. This corresponds to bettors first assessing the probabilities of each horse winning, and then conditional on these probabilities, considers the probability of the runner-up. Note that with unbiased probability perceptions the two frames are equivalent.

As also noted in Snowberg and Wolfers (2010), the rejection of the risk-love explanation implies the rejection of an explanation with misperception of probabilities and gamblers being able to reduce compound lotteries into simple lotteries. We demonstrate this by plotting the probability weighting functions for each market that are required to explain the favorite-longshot bias. In particular we assume that utility of betting on any option is given by

$$\pi(p)(O + 1) = 1 - \tau, \tag{4}$$

[4] We fit non-parametric as well as parametric constant absolute risk aversion utility functions by using the likelihood-based approach of Jullien and Salanie (2000) for both markets. The results display significantly ($p < 0{,}0001$ for parametric estimates) different utility functions across the markets.

where τ denotes the track take. To estimate the weighting function π we need the actual probabilities, which are again obtained by the Loess procedure. To be more precise, we can compute the perceived probability $\pi(p) = (1-\tau)/(O+1)$ directly from the data. Then we use the Loess procedure to estimate the true probability given the perceived probability. The weighting function is then the inverse of that function. Figure 2 plots the obtained probability weighting functions with logarithmic scale.

[INSERT FIGURE 2 HERE]

The logarithmic scale is necessary to distinguish small and tiny probabilities. In principle, the estimated weighting functions explain the favorite-longshot bias by overweighting low probabilities. The bettors therefore perceive a highly unlikely winner being less unlikely than in reality. In this sense the weighting functions are consistent with the decision weights presented in Kahneman and Tversky (1979).

The weighting functions are, however, different across the markets with larger biases for the win market. This should not be surprising since equations (2) and (4) are similarly structured, with the exception of non-linearity entering in different places. Therefore, the fact that the magnitude of the favorite-longshot bias differs between the markets invalidates both the risk-love explanation and the misperception explanation when bettors properly reduce compound lotteries consistent with equation (4). Note that Snowberg and Wolfers (2010), whose analysis is somewhat similar to ours, are unable to observe the exotic market returns and weighting functions because they only use odds of winning combinations at exotic markets.

The logarithmic weighting functions display an S-shape: the curve is convex for small probabilities and turns concave for large probabilities. The existence of an inflection point is contrary to the implications of the information model advocated by Sobel and Raines (2003) in the context of greyhound racing markets. Their model implies a linear relation $\pi(p) = \alpha + \beta p$ between the perceived probability and the objective probability which would imply either a globally concave or globally convex logarithmic weighting function. In particular, the linear relation between probabilities implies that $d^2 \ln \pi / d \ln p^2 = \alpha\beta p/(\alpha + \beta p)^2$, the sign of which is determined by the product $\alpha\beta$.[5]

[5] We also fit a parametric Prelec weighting function for both markets by using the likelihood-based approach of Jullien and Salanie (2010). The estimates display significant ($p < 0{,}0001$) non-linearity in both markets. The weighting functions are also significantly ($p < 0{,}0001$) different across the markets.

Our data also displays the opposite pattern found in Sobel and Raines (2003) in terms of how bet complexity affects the magnitude of the favorite-longshot bias. We find that the favorite-longshot bias becomes less severe as the bet complexity increases, that is the quinella market odds tend to display less bias than the win market odds. In fact, the S-shape of the weighting function is less easily detected in the quinella market because the quinella market seems to be more efficient in our data set.

5. Validation of misperception explanation with failure to reduce compound lotteries

Next we show that misperception of probabilities together with a failure to reduce compound lotteries — as in equation (3) — can account for the difference in the magnitude of the favorite-longshot bias across the win and quinella markets. To accomplish this we use the win market probability weighting function to compute a prediction for the quinella market weighting function (using equation (3)) and show that the predicted weighting function coincides with the actual observed quinella market weighting function.

The arbitrage condition (4) can be used to compute $\pi(p_A)$ and $\pi(p_B)$ directly from the win market data, but $\pi(p_{A|B})$ and $\pi(p_{B|A})$ are more difficult to obtain. We estimate the probability of horse A to place second conditional on horse B winning the race $p_2(\pi_A|\pi_B)$ non-parametrically from the win market data using the two-dimensional Loess procedure. An alternative approach would be to assume conditional independence and use the Harville (1973) formula which means replacing $\pi(p_{A|B})$ with $\pi_A/(1-\pi_B)$. Similar to Snowberg and Wolfers (2010), we opt for the non-parametric estimation in order to use the win market data more efficiently.[6] Figure 3 displays the actual and predicted weighting function for the quinella market with zoomed views of the areas of highest disagreement.

[INSERT FIGURE 3 HERE]

The actual weighting function from using only quinella market data is already presented in Figure 2. To compute the predicted weighting function we first use the win market data to estimate function $\pi(p)$ and then invert it. Denote the estimated function by $\hat{\pi}$ and the estimated inverse by $\hat{p}$. In order to compute the value of the expression in equation (3) we next estimate the non-parametric model for the second place $p_2(\pi_A|\pi_B)$, again using the win market data. The final step is to estimate the plots in Figure 3 with $\pi_A\hat{\pi}(\hat{p}_2(\pi_B|\pi_A)) + \pi_B\hat{\pi}(\hat{p}_2(\pi_A|\pi_B))$ as the dependent variable and

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[6] It is a well-known fact that the Harville formula is biased. This bias occurs because there tends to be more entropy in the race for second place than for first place. This makes favorites who fail to win less likely to finish second than implied by the Harville formula (see Stern 1990).

$\hat{p}(\pi_A)\hat{p}_2(\pi_B|\pi_A) + \hat{p}(\pi_B)\hat{p}_2(\pi_A|\pi_B)$ as the independent variable. Note again that only win market data is used for the predicted weighting function, whereas only quinella market data is used for the actual weighting function.

The close resemblance of the actual and predicted weighting functions, using data from two separate markets, is evidence of bettors having biased probability perceptions and failing to reduce compound lotteries. The result is similar to Snowberg and Wolfers (2010) suggestion, but their data contains only the winning exotic market combinations. This leaves them unable to observe the actual quinella market weighting function. Their strategy is to compare win market based predictions point-wise against the actual odds of winning combinations. In practice, this allows them to conclude that the misperceptions explanation is better than the risk-love explanation. However, they cannot simply reject the risk-love explanation or tell exactly how good the misperceptions explanation is.

Further, the lack of complete set of exotic market odds yields potential selection problems. We have performed an analysis similar to Snowberg and Wolfers and found that in our data set limiting the analysis to only winning combinations affects the results substantially. For example, the percentage of combinations for which the misperceptions explanation yields better predictions increases from 58% to 71% when non-winning combinations are also included. This indicates that also the results of Snowberg and Wolfers may be affected by sample selection issues, though it seems that inclusion of all combinations might make their conclusions even more convincing.

Our main result, the superiority of the misperceptions explanation of the favorite-longshot bias relative to the risk-love explanation, boils down to the observation that the weighting functions of Figure 3 are virtually indistinguishable in comparison to the weighting functions of Figure 2. The question remains how close to a perfect fit we have in Figure 3. Unfortunately inference within the local regression framework requires symmetrically distributed residuals (see Cleveland and Devlin 1988), a feature that our data does not display. Instead, we analyze our results by using a linear regression.

For each quinella market pair in each race, we compute, as explained above, the true probability p_w and perceived probability π_w using win market data with a failure to reduce compound lotteries. We also compute the true probability p_q and perceived probability π_q using quinella market data. Instead of analyzing the implications of the two markets separately and plotting the implied weighting functions — as in Figure 3 — we note that if the implied weighting functions are identical, the only variable that should explain differences across markets in perceived probabilities $\Delta \ln \pi = \ln \pi_w -$

$\ln \pi_q$ is the difference across markets in true probabilities $\Delta \ln p = \ln p_w - \ln p_q$. This suggests estimating a regression model of form

$$\Delta \ln \pi = \alpha + \sum_{i=1}^{3} \beta_i (\Delta \ln p)^i + \sum_{j=1}^{2} \gamma_j \left(\ln p_q\right)^j + \varepsilon, \qquad (5)$$

where the predictors are centered and the degrees of polynomials are limited to three and two to avoid excessive multicollinearity. According to our hypothesis β_1, β_2 and β_3 are the only coefficients that should be non-zero.

Table 1 displays the results of the regression.

[INSERT TABLE 1 HERE]

All estimates differ highly significantly from zero. With a sample size of 1,224,253 combinations this should not be surprising because relatively minor deviations from the proposed relation as well as measurement related issues such as roundings could cause significant relationships. The results, however, display several orders of magnitude smaller and less significant estimates for coefficients on $\ln p_q$ than for coefficients on $\Delta \ln p$ which is in line with our hypothesis. We have also experimented with different specifications both with and without centering of predictors and obtained qualitatively similar results. Overall, we do not find entirely conclusive evidence that the joint behavior of win and quinella market odds is exactly explained by the given form of probability misperception. All of our analysis, however, suggests that the deviations are small in magnitude. In next section we argue that one explanation for the observed deviations might be a different proportion of casual and serious bettors across the markets.

6. Robustness of the results

We examine the robustness of our findings by differentiating between weekend (15,067) and weekday races (5,143) as in Sobel and Raines (2003) and Sobel and Ryan (2008). These papers argued that on weekends there is a higher proportion of casual bettors, while on weekdays serious bettors dominate the markets. They further present evidence that casual bettors tend to favor simple bets whereas serious bettors also participate in the exotic markets.

As another robustness check, we separate the data by country of origin: Finland with 8,923 races and Sweden with 11,287 races. The reason for making this distinction is that in Sweden horse race betting is considerably more popular than in Finland, especially in the win market. The average sales of a

Swedish win market in our data is 19,967 euros, which is more than ten times the Finnish average of 1,981 euros. In the quinella market the situation is more even, with Swedish average sales of 18,467 euros compared to Finnish sales of 12,993 euros. The Finnish win markets may therefore be prone to more inefficiencies than the other markets.

In Figure 4 we use the different sub-samples to plot the actual weighting functions of the quinella market and our prediction based on using win market data, assuming a failure to reduce compound lotteries.

[INSERT FIGURE 4 HERE]

In all of our sub-samples, the prediction matches the actual weighting function relatively well and provides overall support for the misperceptions explanation of the favorite-longshot bias.

It is, however, easy to observe greater deviations for Finland, and for weekends. The deviations seem qualitatively similar in that the win market behavior predicts relatively low perceived probabilities for the favorites in the quinella market. This pattern is consistent with the above-mentioned idea that on weekends casual bettors, who probably place relatively small bets on the favorites, dominate the win market. The pattern is also consistent with the fact that the Finnish win market has, on average, a low volume and is therefore likely to attract less serious bettors than the more lucrative quinella market.

7. Conclusions

In previous studies, it has been difficult to distinguish between probability misperception and risk preferences as explanations of the favorite-longshot bias. We utilize a unique data set from the Finnish and Swedish harness horse race markets to explain the bias. Our results clearly indicate that misperception of probabilities is a better explanation for the favorite-longshot bias than risk-loving preferences. Therefore our results give strong support for the main result of Snowberg and Wolfers (2010). We are, however, able to provide a more direct and convincing analysis because our data set includes odds of all quinella combinations, including the non-winning ones. This feature of our data further allows us to provide direct evidence of a specific type of failure to reduce compound lotteries.

Our paper also adds to the understanding of the psychological frames that are used to assess different lotteries. Kahneman and Tversky (1979) show that preferences appear to be sensitive to representing gambles in a simple or sequential form. We suggest that, in the case of quinella bets, bettors tend to choose a frame that is consistent with a sequential resolution.

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FIGURES

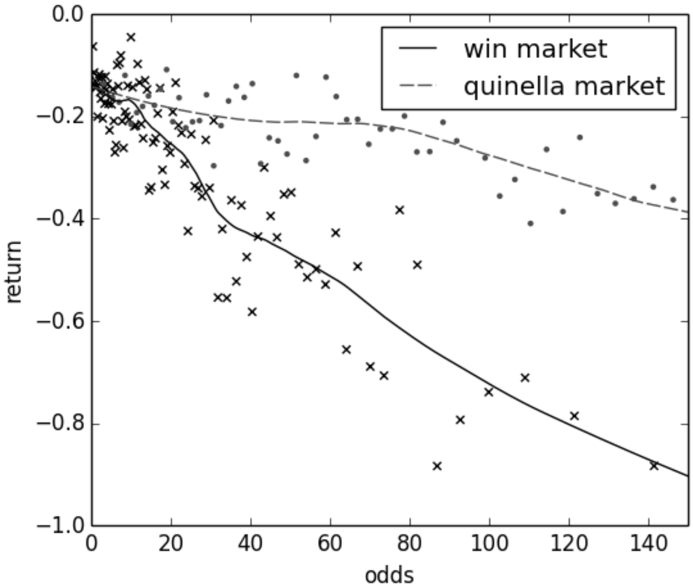

Fig. 1: Differences in the rates of return between win and quinella markets imply that no utility function can rationalize both. The scatter plots represent raw data aggregated into percentiles.

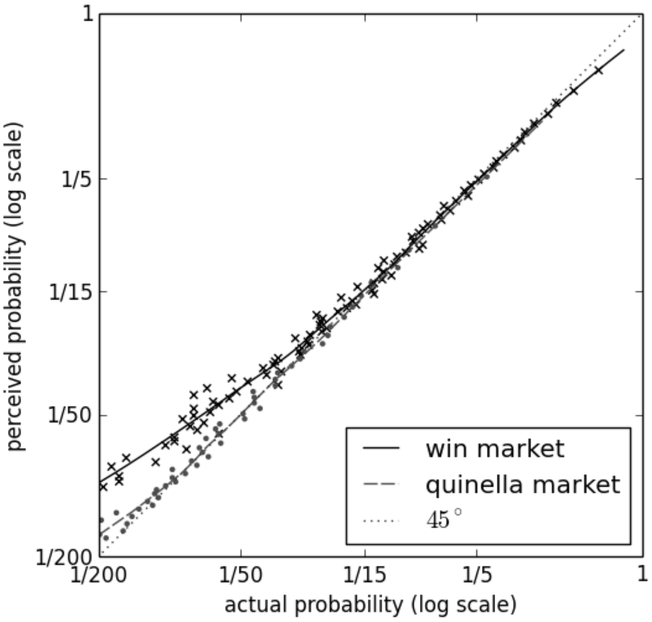

Fig. 2: Probability weighting functions that are consistent with the favorite-longshot bias differ across markets when bettors properly reduce compound lotteries. The scatter plots represent raw data aggregated into percentiles.

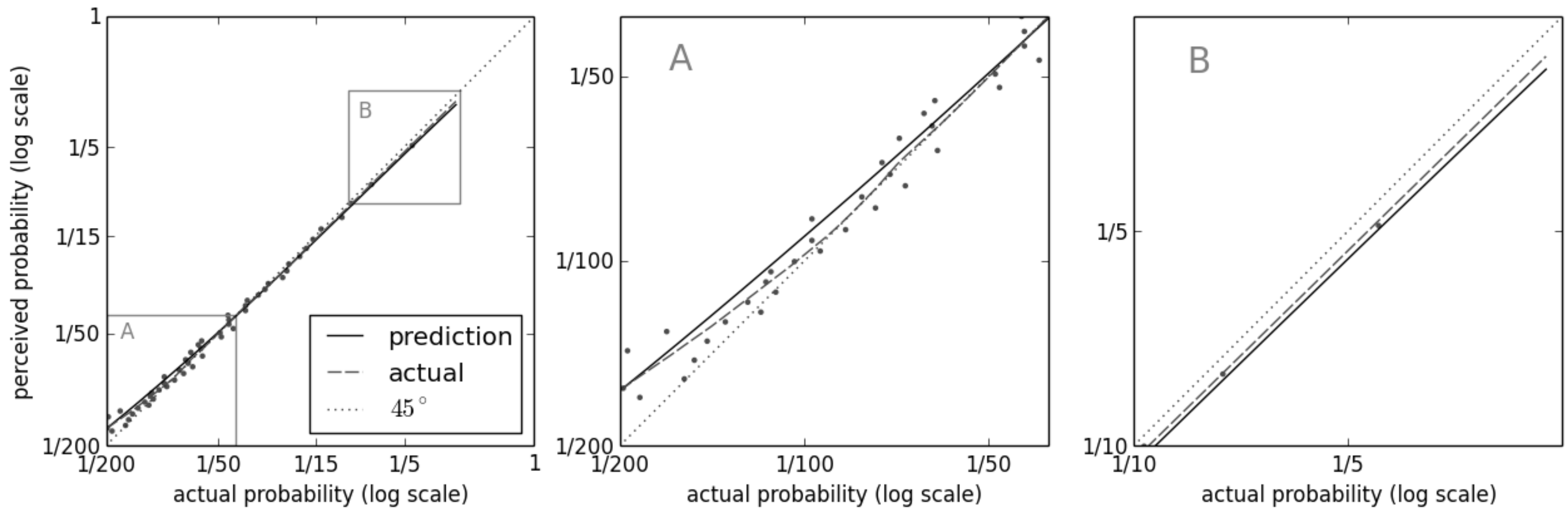

Fig. 3: Misperception of probabilities with a failure to reduce compound lotteries provides an accurate prediction of the quinella market weighting function. The scatter plot represents raw data aggregated into percentiles. Subplots A and B represent zooms over the areas of highest disagreement.

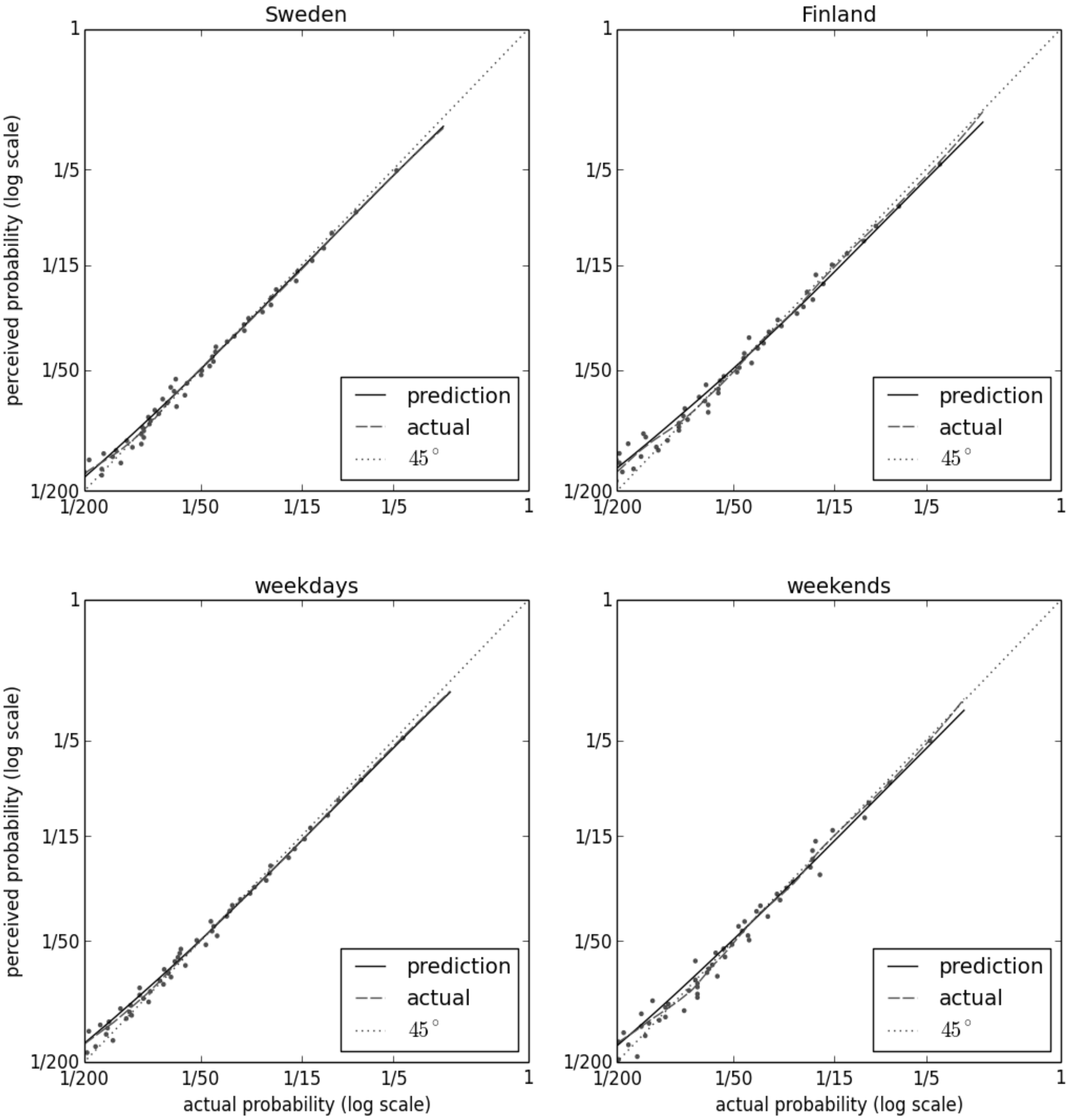

Fig. 4: Coincidence of actual and predicted probability weighting functions is robust to sub-sampling. The scatter plot represents raw data aggregated into percentiles.

TABLES

Table 1. Regression results for differences of probability perceptions

Parameters	Dependent Variable $\Delta \ln \pi$		
	coeff.	*std error*	*t-value*
α	0.0073	0.0001	54
β_1	0.7763	0.0002	4477
β_2	0.0275	0.0001	193
β_3	-0.0055	0.00002	-285
γ_1	0.0070	0.00007	104
γ_2	-0.0006	0.00003	-20
R^2	0.946		
N	1 224 253		