Psychological biases affect economic market prices

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Abstract

A fundamental debate in social sciences concerns whether patterns of individual judgment and choice, resulting from psychological mechanisms, are manifested in collective economic behavior. We examine whether individual bias persists in market prices. Past studies have found that judged likelihoods of possible events vary systematically with the way the event space is partitioned, with probabilities of each of n events biased toward $1/n$. We look for evidence of such bias in various prediction markets, where prices can be interpreted as probabilities of upcoming events. In four studies we find partition-dependence not only in individual judgments but also market prices.

Different social sciences advance fundamentally different views of individual behavior and, consequently, of market misbehavior. When markets produce bad outcomes, as in the recent economic crises, psychologists are inclined to blame individual cognitive biases such as optimism, and emotional forces such as greed and fear. Economists are inclined to maintain that people acted rationally, but political pressures and poorly-designed economic institutions created incentives for rational actors to make decisions that had negative external effects for society. A scientific way to reconcile these competing views is to investigate whether systematic, psychologically plausible mistakes in individual judgment distort behavior in economic markets.

The manifestation of individual bias in aggregate economic and political activity is likely to depend on details of both the underlying psychology and the relevant economic and political institutions. For example, it is well known that there can be a “wisdom of crowds”, in which group predictions are better than those of most individuals in the group [1] through averaging of idiosyncratic errors [2]. In particular, if the distribution of judgments is symmetrically distributed around the true value then the average judgment is expected to coincide with the true value. However, if judgments of group members are biased in a particular direction then the group judgment will remain biased (and could even be more strongly biased).

A market price is a very special kind of “group judgment” in which each trader’s opinions are weighted by their trading activity; confidence has to be backed by money. As a result, even if a large majority of investors make a judgment mistake, if a small number of well-informed and well-capitalized traders do not make that mistake, then the disproportionate influence of their “smart money” could lead to sensible pricing and ideal capital allocation for the entire market.

Unfortunately, this rosy conclusion about markets has been shown to be sensitive to many assumptions about rationality and trading structures [3]. Even sophisticated participants who control huge sums (e.g., mutual fund managers) may be unwilling to boldly bet that market prices they think are distorted will adjust to a correct fundamental price quickly enough to be profitable [4-5].

More generally, economic theory shows that whether small behavioral biases are eliminated or exacerbated by trading activity depends on whether more rational traders have an incentive to trade against those biases to exploit arbitrage opportunities or trade with those biases to profit as their effects grow (as in a price bubble), effectively multiplying their effects [6-9].

Given all these considerations, an ideal test for psychological influences on market activity (or their absence) requires both a well-established, robust psychological pattern of bias in judgment and a market in which that pattern would be clearly revealed by observable economic market data such as prices.

The psychological pattern we explore is how groupings of the set of possible events to be judged influences their perceived likelihood ("partition-dependence", in psychological terms). The markets we explore are "prediction markets" in which prices reflect an aggregate judgment of the likelihood of a set of possible naturally-occurring events. We describe an empirical showdown between the psychological and economic points of view about whether partition-dependence (PD) in individual likelihood judgments will also be evident in market prices. (Roughly speaking: Psychology says "Yes" and economics says "No".)

Prediction markets provide an ideal domain for our empirical test of the persistence of psychological bias in aggregate economic behavior. In prediction markets, financial claims are traded that pay a fixed sum of money when a precisely defined event occurs. For example, on August 14, 2011 a claim on the event "Rick Perry is the Republican Presidential nominee in 2012" traded for $3.40 (it pays $10 if the event occurs). This price implies a collective judgment, on that day, that Rick Perry's nomination has a 34% chance of occurring.

In these markets, the terminal value of assets is ultimately determined by the outcomes of natural events that occur a few months later. "Patient capital" should therefore be willing to buy or sell heavily to correct pricing mistakes, wait a short while for that bet to pay off, and thereby eliminate judgment biases in these markets.

Early prediction markets were based on remarkable experimental evidence that modest amounts of informed trading could lead to prices that "aggregate" information that is dispersed among people [10]. Inspired by these stylized lab examples, the Iowa Experimental Markets (IEM) on political events were created in 1992 [11], followed a decade later by other markets on worldwide current events (e.g., Intrade) and internal markets used in companies to aid in forecasting [12-13].

Prices in prediction markets are usually interpreted as a collective probability assessment, or "crowd wisdom" of event likelihood. These predictions are found to be generally at least as accurate, and often more accurate, than those derived from opinion polls or expert judgments [14-16]. Prediction markets provide an ideal test of partition-dependence because they generally trade an exclusive and exhaustive set of discrete events into which the set of possible state outcomes has been partitioned. Previous studies of these markets — and economic theorizing about prediction markets as well — have assumed that the particular way in which the state space is partitioned should not affect prices. However, if individual judgmental biases influence markets there is ample reason to expect that how partitions are explicitly presented will influence market prices through these individual judgments.

A number of studies of individual judgment show that "unpacking" a single interval $[I_1 \cup I_2]$ into two separate ordered sub-intervals I_1 and I_2, which are logically equivalent, reliably increases its judged probability (i.e. the sum of the judged probabilities $P(I_1)+P(I_2) > P(I_1 \cup I_2)$). Unpacking an interval into its explicit parts seems to draw extra attention to the parts and increase their judged likelihood.

To illustrate, consider the event "the closing value, *X*, of the NASDAQ index will be 2,000 or below on the last day of trading this year." The judged probability of the interval $X <= 2000$ is generally higher when it is broken into two subintervals that are assessed against a single complementary interval (i.e., $\{X <= 1{,}000; 1000 < X <= 2000; X > 2000\}$) than when it is a single interval that is assessed against two complementary intervals (i.e., $\{X <= 2000; 2000 < X <= 3000; X > 3000\}$) (see [17]).

Dependence of judgment on the salient partition of the state space seems to reflect an anchoring of judged probability on a diffuse "ignorance prior" belief at $1/N$ (when there are N explicitly-presented intervals), with insufficient adjustment from the $1/N$ anchor due to limited imagination about how different the intervals are. For instance, in the NASDAQ example above, the interval $X <= 2000$ is two of three events in the first partition (ignorance prior = 2/3) and one of three events in the second partition (ignorance prior = 1/3). This simple $1/N$ hypothesis turns out to be a useful tool for making predictions about when judgment and price errors will be small or large.

Previous evidence of PD has been found in judgments by highly-trained decision analysts [17], in valuation of hypothetical insurance policies which unpack possible causes of death [18], and is robust to learning [19] and financial motivation [17, 20-21] in laboratory experiments. PD is also evident in economic field data on allocations of savings to personal investments [22-23], allocations of capital to businesses in multi-division firms [24-25], and stock price increases when fast-growing parts of a company are "carved out" to be sold separately [26].

We investigate both whether a PD bias exists in individual judgments about naturally-occurring events, and, if so, whether prediction market prices propagate that bias or expunge it. The unique combination of lab experiments, field experiments, and naturally-occurring market data that we report also addresses skepticism in economics about whether psychological lab effects generalize to important economic field settings [27-29].

Study 1: A short lab experiment: Subjects (N=192) traded bets linked to the eventual numerical value of financial, sports, and weather events (in balanced order across groups). The full numerical range for each event value was divided into four intervals. For each of two separate trading groups, either the two lowest-valued intervals or the two highest-valued intervals were combined into a single interval (see the lower part of Fig. 1A for an example). That is, assets linked to two separate intervals I_1 and I_2 were traded by one group, while the single interval equal to their union, $I_1 \cup I_2$, was traded by another group.

Both groups were told about their own partition of intervals and, importantly, they were also told about the other group's partition. This instruction to both groups is essential because (in theory) partition-dependence could result from an inference by traders that (for some reason) the market designer chose partitions that tend toward equal probability; such an inference would coincide with the $1/N$ heuristic. In our design, however, both groups are told about both partitions. Thus, any inferences that participants draw from the choice of the partitions should be the same in both groups so that any difference in the groups' behavior cannot readily be attributed to information conveyed by the choice of partitions.

Because winning bets paid 100 cents, holding one asset for every interval was sure to yield 100 cents when the event's numerical value is determined. To encourage exploitation of pricing mistakes, subjects were allowed at any time to invest 100 cents to buy a portfolio of one share on each event from the experimenter. Thus, if the sum of offered share prices was above 100, low-risk arbitrage was possible. Similarly, arbitrage could be exploited if a set of shares on each event could be bought for less than 100 cents. Such arbitrage was also common; small differences occurred in 85% of markets and were arbitraged in an average of 12.83 seconds (see SOM).

Trading was conducted in two 10-minute rounds for each event, using a customized continuous double auction (CDA). The CDA allows subjects to submit either bids to buy or asks to sell, or to accept current bids and asks to make a trade. Hundreds of experiments have shown that this trading mechanism reveals information reliably and rapidly [30] and creates near-maximum gains from trade [31]. Subjects also expressed their individual beliefs about event probabilities before and after trading, so we could compare those market prices with the distribution of those beliefs, and see if market trading changed their beliefs from before-to-after (Fig. 1A).

Average prediction market prices exhibited a large and persistent degree of partition-dependence (Fig. 1B). For instance, the average of the last three prices was 0.354 for the event "*the max temperature in Muenster at the end of May is in the interval [20°C, 23.9°C]*" and 0.496 for the event "*the max temperature … is 24°C or more*" for the first group. But it was only 0.707 for the event "*the max temperature … is 20°C or more*" for the second group (for a more detailed description of the events see SOM 1.1.). Overall, the difference between the average of the last three prices of unpacked assets and the associated packed asset was .267, .229, and .149 for finance, sports, and weather events, respectively. The differences in individual pre-trading judgments were .312, .261, and .278 for those events. The corresponding differences in individual post-trading judgments were .257, .256, and .226. While all these numbers are close together, the PD gap in prices is clearly closing across time (Fig. 1B) and the post-trading individual beliefs reflect less bias than pre-trading beliefs. These small effects suggest that market trading can actually reduce PD a little (but the reduction is only significant for the weather market, $p=.02$).

Study 2: A multi-week field experiment: We found that the PD effect does shrink a little over the course of the 20-minute trading span in the laboratory experiments of Study 1. This observation motivates a second study of a prediction market involving sporting events that unfold over about eight weeks (N=456 participants). The events are American NBA basketball playoffs (2005-06) and the 2006 soccer World Cup. These prediction markets trade assets over five intervals of total victories by NBA teams, or total goals scored by national teams across the World Cup (in regulation play, excluding shoot-outs). As in Study 1, there were two separate trading groups in which assets linked to goal counts of four teams were traded. In each group, one interval was unpacked into two subinterval assets and another interval (unpacked in their counterpart group) was packed into a single asset. The trading mechanism and all other methods were very similar to those in Study 1 (see SOM), but they were adapted for web access only and trading was possible for several weeks.

The PD effects are similar in magnitude to those in the lab markets. Individual belief judgments summed across unpacked intervals are a median of .20 higher in NBA and .15 higher in World Cup markets than in comparable packed intervals. The sum of market trading prices for two unpacked intervals is persistently higher than the comparable packed-interval price, and there is not much visible convergence over time (see Fig. 2A, for the most actively traded NBA team, the Dallas Mavericks).

Creating an index of the amount of overall PD in these prices is complicated by the fact that liquidity was low. Since there was not always a range of bids and asks at which to trade, what "the price" is at any moment in time is ambiguous. A conservative approach interpolates hypothetical prices by assuming that buyers could always buy at the **higher** of the last price or the next purchase price (and oppositely for sellers). This approach creates a continuous flow of virtual prices, to measure how much could be hypothetically earned by selling assets on two unpacked events and buying the cheaper packed event (called PD arbitrage) or executing the opposite trade (reverse PD; which should never be profitable if PD exists). The time-weighted average hypothetical arbitrage profit is highly variable among teams, but is much higher in exploiting PD effects than exploiting reverse-PD effects (see Fig 2B).

Study 3: Macroeconomic Indicators: Our third dataset is 153 large-scale "economic derivatives" (ED) prediction markets for four macroeconomic indicators, created by Goldman Sachs and Deutsche Bank [32].The markets are parimutuel in structure and were conducted 1-2 days before the indicators were released. We focus on only "digital options" which pay off if the indicator value lies in a specific interval. A full set of digital option market prices for N numerical intervals spanning the entire range reveals an approximate probability distribution for that indicator's likely value (left panel of Fig. 3).

Suppose the observed market prices are equal to the weighted average of a hidden "best guess" (unanchored) price plus a $1/N$ anchor value (Fig 3). Then a simple statistical procedure can be used to impute the weight on the $1/N$ anchor that is implicit in observed prices (for details see SOM). For three of the four indicators, the anchor weight is positive ($p<.10$) and it is strongly positive overall (equal to .44, $p<.01$), once again indicating a PD bias in the predicted direction. A slightly different statistical analysis gives a similar anchor of .39.

Study 4: Horse races: The fourth and final dataset uses horse races. In parimutuel horse racing, bettors buy tickets on horses they think will win. The losers' bets are divided among the winners (after a track takeout). These are prediction markets because the percentage of money bet on each horse is a collective subjective probability of that horse winning. Since "longshot" horses have a low subjective probability, a lot of money is paid out to the relatively few people who bet in the rare event that the longshot wins (i.e., the rate of return, or "odds", are high).

Many studies show that these longshots are overbet relative to their actual chances of winning (and favorites with high probability and low odds are relatively underbet). This tendency is called the "favorite-longshot bias" and is well-established across many countries and decades [33]. Several different explanations have been offered, including frictions that prevent equilibration [34], interaction of information and timing [35-36], a desire for positive skewness bets, and overweighting of the low probabilities of longshots winning [33].

The $1/N$ partition-dependence bias can also explain the favorite-longshot bias, because horses with true probabilities below $1/N$ (the longshots) will be subjectively overestimated if their odds are biased in the direction of a 1/*N* anchor. Uniquely, PD predicts that the size of the longshot bias will vary with the number of horses in a race (*N*) (which is generally 6-12). When there are fewer horses in a race, *N* is smaller and longshots should be more heavily overbet. Detecting this effect statistically requires comparing subjective market probabilities (from actual market betting odds) to actual objective winning frequencies in different probability categories, and then comparing those subject-objective differences across races with different numbers of horses. This has been done with a remarkable sample of all US horse race starts from 1992 to 2001 (6.3 million starts [33]).

The results of this analysis reveal an orderly pattern in which subjective probabilities of longshots are indeed higher in races with fewer horses, exactly as predicted by the PD effect (Figs. 4).

Discussion

A central question in social sciences is how constraints on individual cognition influence collective activity. The default conjecture from psychology is that limits on individual rationality observed in lab experiments are likely to generalize to behavior in more complex market and political settings. The default conjecture from economics is exactly the opposite: Markets and political systems will select more rational agents, or create incentives and organizations that implement greater rationality, in order to make good high-stakes consequential decisions.

There is surprisingly little evidence directly testing these opposing conjectures. Early studies showed that simple mistakes in judging probabilities do affect prices in very simple experimental markets [37-39]. Recent results go further, showing in a few cases that market rules can either amplify individual mistakes (since more rational traders should follow an irrational herd) or dampen them [3,6,8-9].

The present paper presents the first set of experiments to address *both* how psychological judgment biases could influence market prices, and whether lab results of such price effects generalize to comparable field settings. We focus on whether judged probability of a numerical interval is partition-dependent (PD), increasing when the interval is unpacked into equivalent adjacent subintervals and decreasing when the complementary interval is unpacked into a greater number of subintervals.

Two lab experiments and two field data sets measure how much PD is reflected in prediction market prices, which are measures of a collectively judged probability.

All four types of data show substantial and persistent PD in market prices. PD is evident in a short (one hour) lab experiment, in a weeks-long field experiment on NBA and World Cup outcomes, in a very large sample of parimutuel horse race markets, and in a parimutuel prediction market forecasting economic indicators. Combining these data sources is useful for the following reasons: General explanations based on trading frictions [34,36] might apply to parimutuel markets but do not apply to the CDA lab and field markets; explanations based on information conveyed by the choice of partitions in horse race and economic indicator markets are eliminated by the lab experiments; and explanations based on low financial stakes and trader experience are eliminated by the parimutuel field markets. Occam's razor therefore favors the only conclusion that applies to all four data sets, which is that PD in individual judgment also influences market prices.

The common argument that markets work to eliminate judgment errors [27] is clearly not consistent with our data. Nonetheless, it is important to note that prediction markets do have an excellent track record of predicting naturally occurring events (compared to other types of prediction such as political polls). Therefore, while absolute faith in market perfection is misguided, it should be replaced by a healthy respect for both the potential of decentralized markets to make accurate predictions and their possible susceptibility to propagating bias. Recognizing the potential of these markets will require a better understanding of how individual psychology and economic and political institutions interact. We believe that such understanding will lead to improvements in the design of institutions that give rise to more robust markets.

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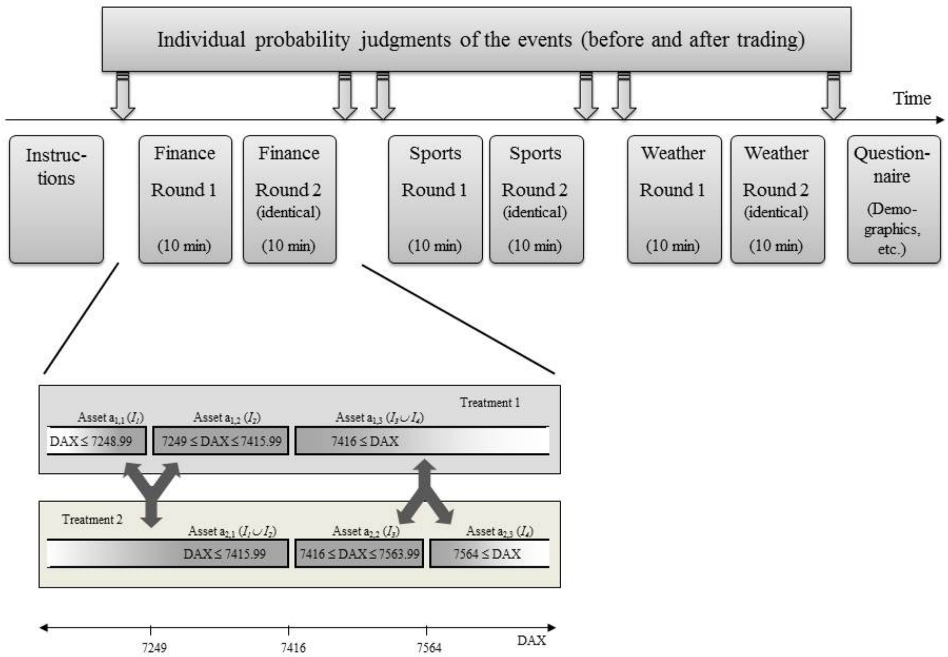
Figure 1. Design and evidence of partition-dependence in a lab experimental prediction market. (A) Time course of a typical experimental session in Study 1 (upper part) and construction of assets for the two DAX partitions (lower part). The digital option will pay a fixed amount (1€) only if the DAX closes within the specified interval two weeks in the future. **(B)** The development over time of price differences of the packed and summed unpacked assets, for the sports assets in Study 1. Prices are averaged over all twelve market replications. The difference in the final prices is significant (Kruskal-Wallis, $p < .001$). The slope of the time trend for the difference in prices is .0094 (top) and .0159 (bottom).

Figure 2. Prices and pseudo-arbitrage profit opportunities in NBA and World Cup field experimental markets. (A) Price chart for packed and unpacked assets in prediction market trading the number of wins by the Dallas Mavericks, DAL. **(B)** For each NBA playoff team, average levels of PD arbitrage are positive and typically larger than reverse PD arbitrage (which is often zero). (Reverse) PD arbitrage occurs if a hypothetical profit could be made by buying the packed event in the one market and selling the unpacked events in the other market (and vice versa). At times where no bids or asks were available, the more conservative from the previous and subsequent price are used, i.e. the price that makes the occurrence of (reverse) PD arbitrage less likely. Levels are set to 0 if no arbitrage opportunity existed. The numbers displayed in the Figure are the time weighted averages of the available PD (or reverse PD) arbitrage levels over the complete trading period.

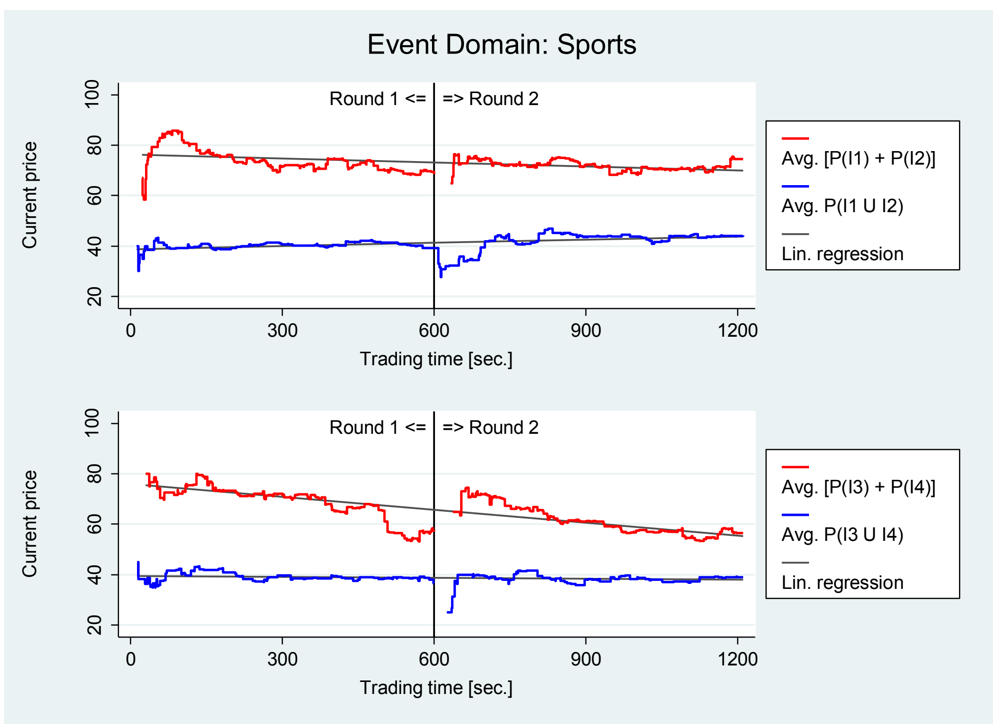
Figure 3: Graphical illustration of a mixture model of prediction market prices. The mixture model assumes that the probability distribution observed in the prediction market is a linear mixture of an unbiased distribution reflecting traders' best guesses with weight $1-\lambda$ (bottom right) and a naïve prior distribution (with weight λ) that assigns equal probability to each subinterval and is thus partition dependent.

Figure 4. The relation between "actual" (sample relative frequencies) and perceived probability (estimated from aggregate market betting) for races with different numbers of horses. $1/N$ bias predicts the curve from races with fewer horses will lie above the curve from races with more horses. Figure reprinted from Snowberg and Wolfers (2010).

FIGURE 1

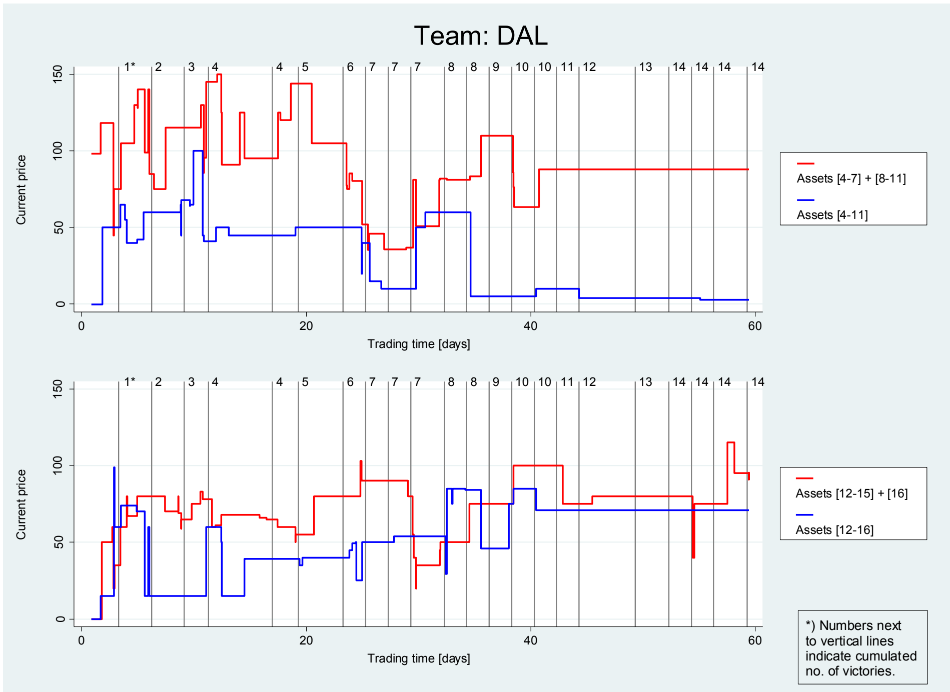

Individual probability judgments of the events (before and after trading)
Time
Instruc-
tions
Finance
Round 1
(10 min)
Finance
Round 2
(identical)
(10 min)
Sports
Round 1
(10 min)
Sports
Round 2
(identical)
(10 min)
Weather
Round 1
(10 min)
Weather
Round 2
(identical)
(10 min)
Question-
naire
(Demo-
graphics,
etc.)
Treatment 1
Asset $a_{1,1}$ (I_1)
Asset $a_{1,2}$ (I_2)
Asset $a_{1,3}$ ($I_3 \cup I_4$)
DAX ≤ 7248.99
7249 ≤ DAX ≤ 7415.99
7416 ≤ DAX
Treatment 2
Asset $a_{2,1}$ ($I_1 \cup I_2$)
Asset $a_{2,2}$ (I_3)
Asset $a_{2,3}$ (I_4)
DAX ≤ 7415.99
7416 ≤ DAX ≤ 7563.99
7564 ≤ DAX
7249
7416
7564
DAX

(A)

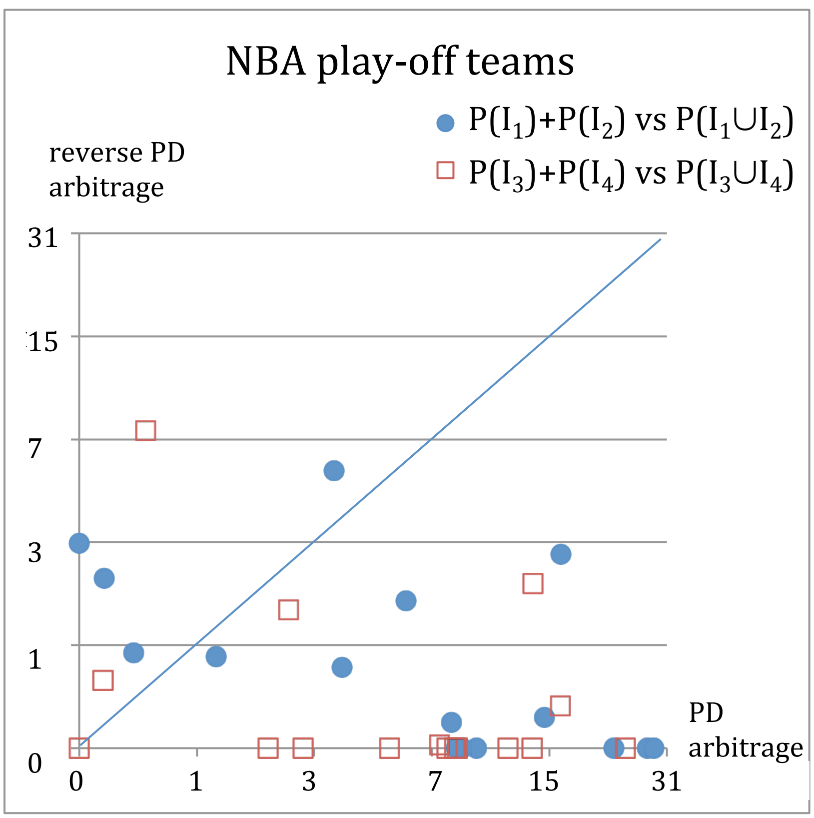

Event Domain: Sports
Round 1 <= | => Round 2
Current price
20
40
60
80
100
0
300
600
900
1200
Trading time [sec.]
Avg. [P(I1) + P(I2)]
Avg. P(I1 U I2)
Lin. regression
Round 1 <= | => Round 2
Current price
Trading time [sec.]
Avg. [P(I3) + P(I4)]
Avg. P(I3 U I4)
Lin. regression

(B)

FIGURE 2

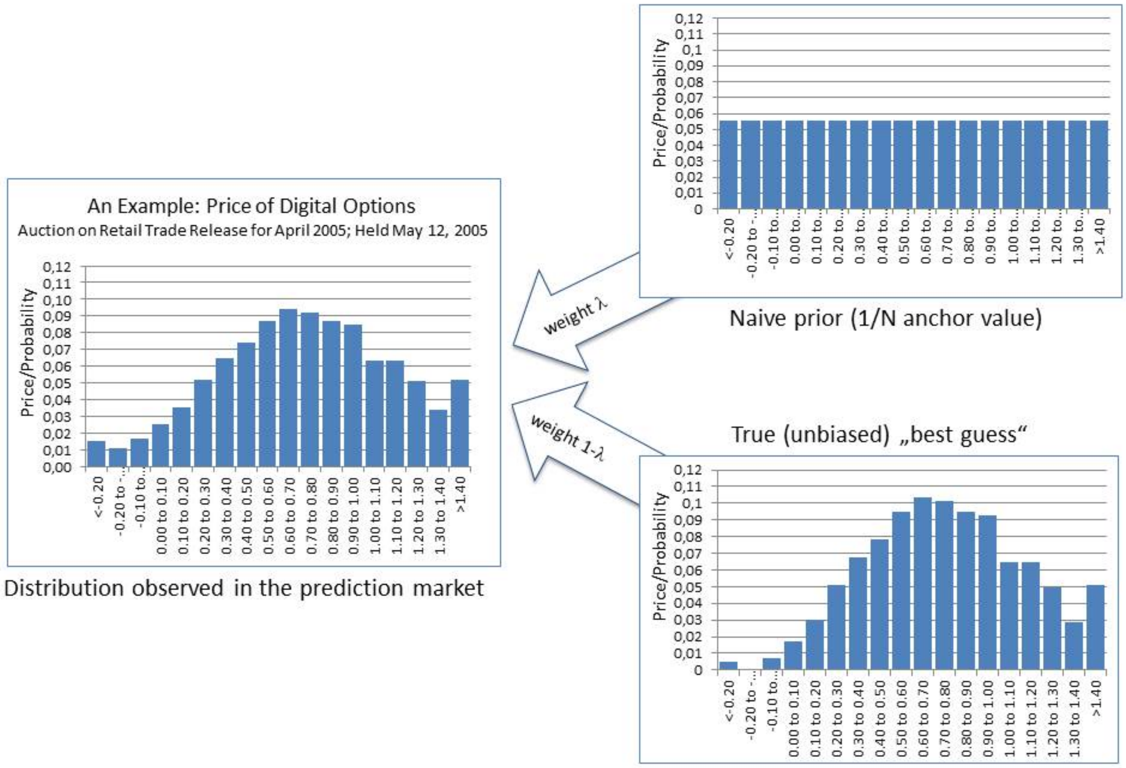

Team: DAL
Current price
Trading time [days]
Assets [4-7] + [8-11]
Assets [4-11]
Assets [12-15] + [16]
Assets [12-16]
*) Numbers next to vertical lines indicate cumulated no. of victories.

(A)


NBA play-off teams
$P(I_1)+P(I_2)$ vs $P(I_1 \cup I_2)$
$P(I_3)+P(I_4)$ vs $P(I_3 \cup I_4)$
reverse PD arbitrage
PD arbitrage
31
15
7
3
1
0
0
1
3
7
15
31

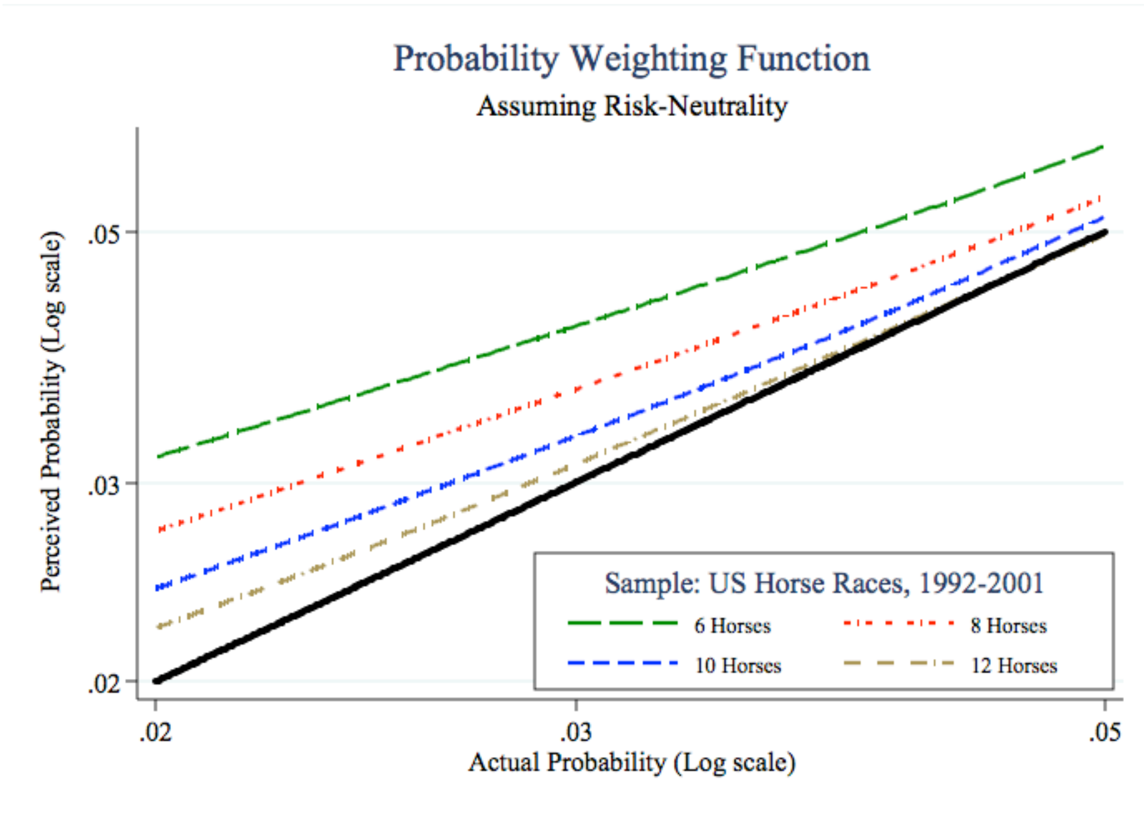
(B)

FIGURE 3



An Example: Price of Digital Options
Auction on Retail Trade Release for April 2005; Held May 12, 2005
Price/Probability
<-0.20
-0.20 to -...
-0.10 to...
0.00 to 0.10
0.10 to 0.20
0.20 to 0.30
0.30 to 0.40
0.40 to 0.50
0.50 to 0.60
0.60 to 0.70
0.70 to 0.80
0.80 to 0.90
0.90 to 1.00
1.00 to 1.10
1.10 to 1.20
1.20 to 1.30
1.30 to 1.40
>1.40
Distribution observed in the prediction market
weight λ
weight 1-λ
Naive prior (1/N anchor value)
True (unbiased) „best guess“

FIGURE 4



Probability Weighting Function
Assuming Risk-Neutrality
Perceived Probability (Log scale)
.05
.03
.02
.02
.03
.05
Actual Probability (Log scale)
Sample: US Horse Races, 1992-2001
6 Horses
8 Horses
10 Horses
12 Horses