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THE PRICE OF RUNNING LIQUID PREDICTION MARKETS

Christian Slamka¹

Abstract

Prediction markets have widely emerged, especially in corporate settings. In order to overcome the perpetual problem of illiquidity, many prediction markets apply so-called automated market makers as market mechanism for trading. However, because they usually need a subsidy to work, they only have been used in play-money markets, where no real money is at stake and losses for operators cannot occur. In this paper, we analyze the only two automated market makers with upper-bounded losses and study maximum and expected subsidies. For PM operators, these amounts to subsidize markets can potentially be compared against the costs of running pure play-money markets.

1. Introduction and Problem

In recent years, interest for prediction markets (PMs) as a promising tool for forecasting has steadily risen. These markets, which started off as a niche application in the field of political forecasting [e.g. [5]], have continuously found applications in further areas such as sports forecasting [e.g. [13]] and also have continued their way into many company-related forecasting fields such as sales forecasting [2], new product concept evaluation [17], or even generation and evaluation of ideas within companies [20]. The reason for their emergence is mainly, besides further advantages such as cost-effectiveness and scalability [19], the high forecasting accuracy. Several studies show that PMs, in terms of accuracy, are mostly superior to other, comparable forecasting techniques such as polls [1], official company forecasts [2], or experts ratings [18].

When designing and running PMs, in general, two very distinct types of PMs can be distinguished: play- and real-money markets [18]. The former markets use a virtual currency, which does not correspond to any real currency, for trading. Based on the traders' performances in terms of play-money portfolio value, usually prizes are given away to the most successful traders. Consequently, traders have an incentive to perform well, i.e. to input their subjectively best predictions into market forecasts. While these prizes do not necessarily have to be high-valued, or even do not have to exist in some cases [3], it is generally believed that some form of incentive to perform well has to be present [18], with values ranging up to several thousand Euros [14]. With the latter type, real-money markets, traders invest their own, real money in the markets. As a result, they are incentivized to make profits with the money they have invested [13]. From a PM operator's

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perspective, using real money is likely to be preferred from the point of view that he does not have to provide any incentives for participation as he would have to when running play money markets. Thus, he would save immediate costs for the incentives as well as costs such as handling the incentives ²). Additionally, more traders might be attracted to these markets, generating more trading activity. Furthermore, less knowledgeable traders might be prevented from entering these markets due to aversion to lose money.

At the same time, besides choosing among real- or play-money, a PM operator must decide on another, crucial question of which underlying market mechanism to use. That is, how to match demand and supply influencing the price of the stocks and therewith, predictions. Earlier PMs such as the (real-money) Iowa Electronic Markets [1] and also most financial exchanges such as the Frankfurt Stock Exchange, employ a standard *continuous double auction (CDA)*, which matches orders of sellers and buyers. Because the CDA does not engage in the transaction itself, which is executed only among market participants, running a CDA is essentially free of financial risk for the operator as he will not suffer any losses. Understandably, this is one of the main reasons why large real-money exchanges, such as *Betfair*, employ it in their trading system.

However, in many small, mainly company-internal PMs, the number of traders in markets is very low or the number of stocks per trader is very high [8]. This essentially leads to a “chicken-and-egg problem”: traders are attracted to liquid markets, i.e. markets with a high trading frequency, but on the other hand, liquid markets require many traders [11]. Because of this illiquidity problem, many PMs use so-called *automated market makers (AMMs)* as a counterpart for trading. In contrast to the CDA, transactions using AMMs do not occur among market participants, but between the AMM as a piece of software and participants in each buy or sell transaction [8; 11]. By providing instant buy and sell opportunities at transparent prices, participants do not have to wait for matching counteroffers for their offers to be executed. So far, companies such as *Microsoft*, *Yahoo!*, *Inklings*, or the *Hollywood Stock Exchange* are using AMMs for trading in their *play-money* exchanges.

Conversely, in contrast to CDAs, possible losses for operators of AMMs are able to occur. Thus, operators usually have to subsidize the market with a certain amount of money which they will lose in order for the PM to work. While losses do not play a role in play-money markets, they could be harmful when running real-money markets with an AMM. This is most likely the reason no company has started using AMMs with real-money markets yet. Then again, even play-money markets cannot be run for free, as traders have to be incentivized with potentially high prizes to trade in the markets. Consequently, it might even be cheaper to run real-money markets with a subsidized AMM than running play-money markets with giving out prizes. However, it is essential for operators to know in advance with how much money they will have to subsidize the market with at most, and have an upper bound on subsidies, i.e. losses. So for PM operators, a crucial task is to implement a market mechanism which assures a strict bound on the maximum loss and will not let losses potentially grow to infinity. While AMMs as described in [21] or [9] do not have a bounded loss, only the *market scoring rules* [8] by Hanson and the *dynamic pari-mutuel market* by Pennock [11] have pre-determined upper bounds on their losses. Nonetheless, to the best of our knowledge, there has been no evaluation this far on a) what the maximum losses running either AMM are, and, b) what the average losses are in order to achieve good forecasting results. Our objective is to answer these two questions by conducting a simulation study, enriched with data from a real-world, real-money PM. In chapter 2, we describe the two focal mechanisms and their functioning. Subsequently, we describe the market model we use for our evaluations. In chapter 4,

² Please note that legal barriers in some countries might restrict the use of real money. This restriction, however, is not discussed in this paper.

we outline the design of the simulation study, followed by the results we obtained in chapter 5. In chapter 6, we draw the conclusions.

2. Descriptions of Mechanisms

Both mechanisms we analyze are parameterized with a single parameter each. These parameters both control the maximum amount an operator can lose when running the markets, as well as the liquidity of the markets, i.e. the speed at which the stock prices move. The higher the parameter values, the higher the possible maximum losses, i.e. subsidies, and the slower the prices move. In order to make this fact clearer, consider a stock which is currently valued rather low. Consequently, the AMM offers shares of stock at a low price, and traders buy shares. Now after the close of the market, supposed the stocks are valued significantly higher than the AMM has sold them for to traders, the operator loses money as he has to buy back the shares from the traders at this high price, which is the current loss. Now supposed the liquidity parameter value is lower, the prices for shares rise more quickly, i.e. traders have to pay more for a share than they would have to with a high liquidity parameter value. In consequence, this means that the losses are lower in this case as fewer “cheap” shares are sold.

2.1. (Logarithmic) Market Scoring Rules

Market scoring rules (MSRs) build up on the long-known concept of *scoring rules*, which have been used to evaluate a forecaster’s performance [e.g. [22]]. By being evaluated with scoring rules, forecasters are incentivized to reveal their subjectively most accurate predictions. With simple scoring rules, forecasters give isolated, one-time predictions, such as the prediction if it rains on a specific day in the future. However, the basic, but ground-braking idea of Hanson’s market scoring rules [8] is that forecasters give successive predictions on one particular forecasting goal by adjusting the former, most current, prediction and giving the second-to-last predictor the amount this forecaster has betted. The amount this forecaster receives for his prediction is the *improvement* of prediction. This number, which can be negative, if it turns out the forecaster has moved the prediction in the “wrong” direction, i.e., farther away from the actual outcome than his predecessor has forecasted. The concept of moving estimates can be modeled by introducing shares of underlying events which can be traded, and have a final value of \$1, if the particular event happens, and \$0, otherwise. With an underlying continuous price function, which is derived from the particular scoring rule being used, the MSR determines the price for each share which is sold or bought. The number of bought shares is positively correlated with the price of shares.

In general, MSRs work with a set of N mutually exclusive and exhaustive outcomes, such that the probabilities of all outcomes sum up to one at any point in time a market is running. While in theory, any proper scoring can be used for market scoring rules, the logarithmic scoring rule $s(p) = b \log(p)$ [8] has been applied in the wide majority of cases, which include the markets of Inkling or Microsoft’s internal markets. The *subsidy* b controls the *maximum* amount of money the AMM can lose as well as the liquidity in the market. Because forecasters pay off the last forecaster before them according to the scoring rule, the operator only has to reimburse the last forecaster for his predictions. Additionally, the very first forecaster has already paid the *initial* amount at the very first trade. Thus, the losses are:

$$\text{loss}^{LMSR} = b \cdot \ln p_{last} - b \cdot \ln p_{ini} = b \cdot \ln p_{last} + b \cdot \ln \frac{1}{p_{ini}} \leq b \cdot \ln \frac{1}{p_{ini}^{p_{ini}=1/N}} = b \cdot \ln N \quad (1).$$

The loss' upper bound of $b \cdot \ln N$ is reached if and only if each share's price is, during market trading, driven to the final payoff³). For instance, if traders in the market very strongly believe that an event will happen, they drive the prices of the share very close to 1, implying a prediction of almost 100% that the event will happen. If now the event actually happens, the operator has to pay off the last trader according to the logarithmic scoring rule.

2.2. Dynamic Pari-Mutuel Market

Standard pari-mutuel markets are known from e.g. horse races and are recognized to be able to aggregate information efficiently at one point in time [16]. At any time before the close of the market, money can be spent on each of the N mutually exclusive and exhaustive outcomes, e.g. on the victory of a particular horse. After the close of the market, the total money spent on all possible outcomes is $M = \sum_{j \in N} m_j$, where m_j is the amount betted on outcome j . When the final outcome is

known, each Euro invested in the "correct" event i is then worth $\frac{M}{m_i} \epsilon \geq 1\epsilon$. But pari-mutuel

markets are not able to update predictions on the arrival of new information, such as news [11]. However in PMs, an update of prediction as a reaction to news is a crucial feature, as the "value" of an event can be determined [15]. This is because participants in pari-mutuel markets are not incentivized to trade before the close of the market, since regardless of the point in time of the investment, a share of the outcome will be equally expensive if bought long before the close of the market. Consequently, reacting to events before the close of the market cannot be achieved with this mechanism.

The dynamic pari-mutuel market (*DPM*, [11]), which is e.g. applied in the Yahoo! Buzz markets, overcomes this problem by introducing dynamic prices for shares of the final amount of money, rather than having a fixed price as with the standard mechanism. The price of a share depends, similar to the MSRs, on the number of shares in the market and on the utilized price function [12]. As in the standard pari-mutuel market, all money is redistributed over all winning shares and the price of a share does not directly correspond to actual probabilities, but has to be transformed into probabilities. When starting the market and in order to allow for trading, an initial amount of

$C(\mathbf{q}^{ini}) = M^{ini}$ and a vector \mathbf{q}^{ini} of shares containing quantities of each must be assigned⁴). The

price function $C(\cdot)$ denotes a 1-to-1 mapping between the vector of shares and the money in the market [12]. Similarly to the subsidy b seen with MSRs, the initial assignment of money/shares controls the liquidity of the market and maximum losses. At the close of the market, there are

$|\mathbf{q}^{final}|$ shares on the market, with corresponding money $C(\mathbf{q}^{final})$ totally invested in the shares. Now

if the event which occurs out of the N events is i , all the money invested in all shares is equally split among the holders of the share. Thus the value of the share of the occurring event i is $\frac{M^{final}}{q_i^{final}}$, where

M^{final} denotes the total amount of money invested in all shares, including the seed money, and q_i^{final} is the final number of shares of i in the market. The amount of shares of i the operator holds at the end of the market is $\min\{q_i^{ini}, q_i^{final}\}$ because the maximum number of shares is either the

³ We make the assumption that with N shares, each share is initialized to the equal price of $1/N$.

⁴ As with the MSR, we assume all N events to be equally likely and, thus, the elements of the initial vector of number of shares are equal.

initially assigned number of shares, or, if more shares have been sold than bought, the final number of shares. Consequently, the loss for the operator is

$$\text{loss}^{DPM} = M^{ini} - \min\{q_i^{ini}, q_i^{final}\} \cdot \frac{M^{final}}{q_i^{final}} \leq M^{ini} \quad (2),$$

and thus, the upper bound of loss is M^{ini} , which is the amount initially invested.

3. Market Model

As a basis for our simulations, we introduce a microstructure market model uniquely designed for AMMs in PMs which we have obtained by extending a model introduced by Das [4], which itself is an extended model of Glosten and Milgrom [7]. The contributed extension of the model (section 3.2) is necessary due to PM- and AMM-specific properties of the markets, i.e. the existence of two stocks in a market and the varying order quantities as opposed to one stock and a fixed order quantity, respectively.

3.1. Basic model

In the basic model of Das [4], one single stock in the market exists which can only be traded by intermediation of a market maker, i.e. one transaction side is always the market maker, and the opposite side is always a trader. Traders in the market arrive one by one in discrete points in time $t \in \{1, \dots, T\}$. The size of a trade is fixed to one unit each trade, in every period the market maker issues bid and ask prices for one unit, $P_{t,b}$ and $P_{t,a}$, respectively. The stock has an underlying true value of V_t , which is exogenously given. There are three types of risk-neutral traders: perfectly informed traders which are exactly aware of the stock's true value V_t , noisy informed traders which receive a noisy signal with mean zero on average, and totally uninformed traders who have a purely random valuation of the stock. Thus, a single trader receives the following signal of the stock's valuation:

$$W_t = \begin{cases} V_t, & \text{if trader } t \text{ informed,} \\ V_t + N(0, \sigma_{noisy}), & \text{if trader } t \text{ noisy informed,} \\ \text{random,} & \text{if trader } t \text{ uninformed} \end{cases} \quad (3).$$

In consequence, a traders issues a sell order if $W_t < P_{t,b}$, i.e. he assumes the stock to be overvalued or issues a buy order if $W_t > P_{t,a}$ for an (subjectively) undervalued share. If the signal lies within the spread, such that $P_{t,b} \leq W_t \leq P_{t,a}$, no order is issued.

3.2. Contributed extension of the model

In PMs, several market designs exists [18], whereas the “winner-takes-all” market is the most common design and also, is supported by both MSR and DPM. In this market design, at least two stocks exist where in the end, exactly one stock “wins”, i.e. the underlying event actually occurs. A classic example would be horse races with e.g. two stocks of two horses, of which one will win, denoted by S_1 and S_2 . This implies that the market model has to be extended to two stocks, which is the simplest form of a multi-outcome, winner-takes-all market. The *true values* V_1 of S_1 and V_2 of

S_2 denote the probability of a S_1 or S_2 , respectively, to win, and are constant in this model. The probabilities of winning, and thus, the true values, always sum up to 1, such that $V_2 = 1 - V_1$ in every period. All traders are assumed to be aware of this property, which implies that we can infer that the signal of S_2 , $W_{2,t}$, can be obtained by calculating $W_{2,t} = 1 - W_{1,t}$ (which equal the stock prices and thus probabilities in case of MSR and the implied probabilities in case of DPM). The choice of a buy or sell order is given. If a buy order is chosen, the undervalued share (relative to $W_{i,t}$) is traded, if a sell order is chosen, the overvalued share is traded.

The second extension of the model aims at the restriction of the trading quantity to one stock per period, which we suspend because different order quantities are essential for the price movements of the AMMs. Due to this relaxation, the decision problem of the trader is not only tied to the question of selling or buying the stock, but also to which quantity. In order to determine the number of stocks to trade, we assume that the risk-neutral trader tries to maximize its expected utility [6] for a stock $i \in \{1, 2\}$ in a particular trade. Thus, for the MSR and in case of a purchase, a trader buys shares until the price per share is above the trader's valuation. By doing this, a trader maximizes his expected utility in a trade. As prices do not directly correspond to probabilities in the DPM and expected payoffs also have to be considered, a similar analyses has been made in [10, lemma 5], in which the authors show how a risk-neutral trader maximizes his surplus when trading with the DPM. Additionally, in order to obtain a more realistic setting, we set a maximum amount c_t as budget constraint to limit the maximum amount a trader can spend (in case of a buy order) or redeem (in case of a sell order). Thus, (here in case of a buy order), the total cost of a buy order has to be below c_t , while the total redemption value of a sell order is also below c_t .

4. Design of Simulation Study

The general idea of the design of the simulation study is to determine the amount of money which the market has to be subsidized with in order to obtain the best possible forecasting result. As the amount of subsidy is positively correlated with the liquidity with both AMMs, we try to find the optimal amount of subsidy which neither provides too much (slow moving (implied) probabilities) nor too low (fast moving (implied) probabilities) liquidity. If we only tried to minimize the amount of money to subsidize the market with, market results would very likely be useless, as little money to subsidize implies very volatile markets which would have no use as a forecasting instrument. So we assume that the top priority for PM operators in the long run is to achieve good forecasting results and thereafter, analyze the subsidies needed to arrive at these results. By *goodness* of a result we denote the prediction accuracy of the actual outcome at the close of a market, i.e. the last prediction. We use the *root mean squared error (RMSE)* over all replications of a certain AMM parameter combination, which is calculated as the root of the mean squared difference of the actual market prediction, namely the probability $prob_{1,T,r}$, and the true value $V_{1,r}$:

$$RMSE = \sqrt{\frac{1}{\#replications} \sum_{r \in \{1, \dots, \#replications\}} (prob_{1,T,r} - V_{1,r})^2} \quad (4).$$

The study's parameter selections are illustrated in Table 1. Because we deal with real-money markets, we assume that only perfectly informed as well as noisy-informed trading exist, each with equal probability of 0.5 of occurrence [4]. If noisy trading occurs, then the standard deviation from the true value, σ_{noisy} , is 0.05, or 5 percentage points. This value has for instance been used by Das [4]. Now in order to capture the effect of an increasing flow of money into the market, we set the

probability of a buy order to occur to $0.6 > 0.5$, leaving a chance of 0.4 of a sell order to occur in a trading period. This value could also be observed in experimental runs in university-internal tests. We are confident that these parameter selections are robust to deviations as we try to find the optimal AMM parameter values by the *final* error. Thus, deviations in simulation parameter will change the absolute level of error, but not the resulting optimal AMM parameter selection.

Parameter	Value/distribution	Random values drawn in each
Probability of informed trading	0.5	replication and period
Distribution of deviation from true value (noise)	N(0,0.05)	replication and period
Probability of buy order	0.6	replication and period
Max. amount to buy/redeem from Bluevex data set	U(0,1)	replication and period
Stock's constant true value	U(0,1)	replication
Number of periods	100 and 1000	
Replications per case	1000	

Table 1: Experimental factors in the simulation study

For the determination of the maximum amount to spend/redeem per trade, we have used actual data from a real-money exchange (*Bluevex*) of the European soccer championships 2004 which used a CDA. Descriptives on the data can be found in [15]. For each game, there has been a market with three stocks: “Team 1 wins”, “Team 2 wins” or “Draw”, each paying 10 € if the event happened. In order to fit the data to our problem, we only considered the shares of the team wins in our data. Also, we have divided all pricing data by 10, as the payoff in this study is 1 € rather than 10 €. We selected the amount bid in each transaction as one data point, resulting in 74,086 data points for both buy and sell transactions. We randomly chose among the values of each order type, each value being equally likely to be drawn. As we do not set any priors on the true value of stock, we thus assume every true value of the stock S_t , V_t , to be equally likely in the range of 0 to 1. We have set the number of trading periods to 100 as displayed. However, we have varied the number of trading periods to 1000, whose results we do not display due to space limitations. They are discussed at the end of section 5. In total, we conduct 1000 replications per AMM / parameter selection case, asserting a plethora of possible market situations.

5. Results

As our first goal is to obtain optimal parameter values with respect to the lowest RMSE of the prediction of the last trade, we applied a manual iterative procedure to determine them. We optimized to the point an integer number for the subsidy or seed money, respectively, was found.

	LMSR	DPM
Optimal parameter	Subsidy = 20 €	Seed money = 25 €
Obtained RMSE	2.804	2.765
<i>Theoretical max. loss</i>	13.86 €	25 €

Table 2: Optimal parameter values and implications for theoretical maximum losses (100 periods)

As it can be inferred from Table 2 (only 100 periods case shown), a subsidy of 20 € for the LMSR and 25 € seed money for the DPM, respectively, minimize the RMSE. The error value is slightly, but not significantly ($p > 0.1$, paired t-test) lower (0.039) for the DPM compared to the LMSR. Thus,

regarding prediction accuracy, both AMMs do not differ. We can now, according to equations (1) and (2), calculate the theoretical maximum losses, which are 13.86 € (= $20 \cdot \ln(2)$) for the LMSR and 25 € (complete seed money) for the DPM. So these are the upper maximum bounds of money a PM operator could lose in theory. Thus, at first sight, the LMSR seems to be superior in terms of maximum possible losses, as 13.86 € \ll 25 €.

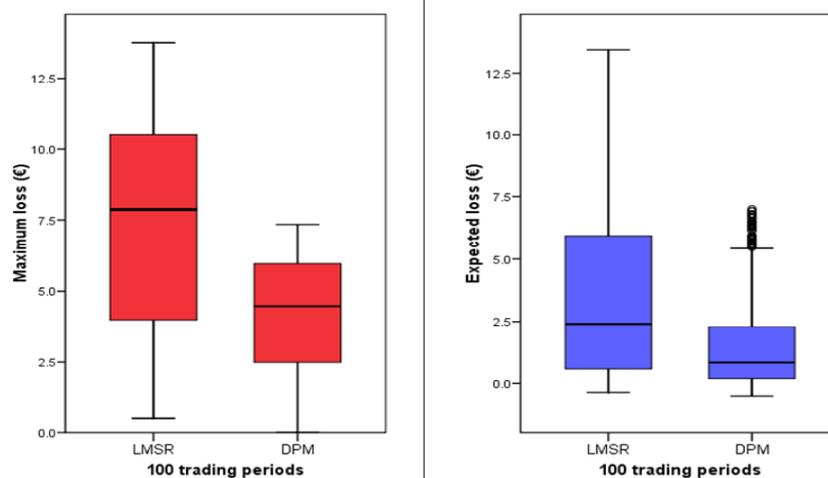


Figure 2: Maximum and expected losses for each AMM (100 periods)

However, although the LMSR has lower theoretical losses, the upper bounds in equations (1) and (2) might not be equally strict. So in the DPM's bound, the values of the remaining shares which the operator has in its portfolio and which might be valued at a price greater than zero, are not considered. Thus, in order to arrive at a more realistic setting, we analyze both maximum and expected losses which can occur given a final state of the market and possible outcomes (either S_1 or S_2 wins) with respective probabilities as true value of a share. The results are depicted as box plots in Figure 2 and Table 3. The maximum losses when considering simulation market data are significantly ($p < 0.001$) higher for the LMSR. The median/mean worst loss of the DPM with 100 periods is 4.48/4.18 €, while it is 7.86/7.36 € for the LMSR. Also, the maximum possible loss which could be encountered is only 7.35 € with the DPM, as opposed to 13.75 € with the LMSR. Notably, the 7.35 € losses of the DPM of the theoretical losses (see Table 3) are only 29.4 % of the maximum, implying a very high upper bound on theoretical losses stated by equation (2). On the other hand, the maximum losses of the LMSR are 99.21 %, and thus, close to the maximum theoretical loss. In practice, this means that when initializing a PM and pre-calculating theoretical losses, with the LMSR the losses can be as high as more than 90 % of the theoretical loss, while with the DPM, a single loss will be no more than roughly 30 % of the theoretical loss (Table 3).

	LMSR	DPM
Maximum losses /	13.75 €	7.35 €
% of theoretical max. loss	99.21 %	29.40 %
Expected avg. losses /	3.66 €	1.50 €
% of theoretical max. loss	26.41 %	6.00 %

Table 3: Absolute and relative maximum and mean expected losses (100 periods)

Besides the *maximum* losses, a PM operator should also be interested in the *expected* losses, when e.g. running several markets. The expected losses include the respective winning probabilities of the shares that can be calculated as follows (for a replication r):

$$loss_{exp}^{LMSR/DPM} = V_1 \cdot loss_{S1_wins}^{LMSR/DPM} + V_2 \cdot loss_{S2_wins}^{LMSR/DPM} \quad (5)$$

The expected median/mean losses for the DPM periods are 0.94/1.50 €, while they are significantly higher with 2.41/3.66 € for the LMSR (right boxes in Figure 2). According to Table 3, the losses which can be expected are about a quarter of the theoretical loss for the LMSR, while they are under 10 % for the DPM of the maximum theoretical loss. We have also conducted the same simulation study with 1000 instead of 100 periods. It turns out that the losses behave roughly linearly with respect to the number of periods in both AMM cases. E.g., the average expected loss for the LMSR/DPM is 47.06/16.31 €, which are factors of 12.9/10.9 with 10 times the number of trading periods. However, in order to find more support for this statement, future research should more thoroughly vary the number of trading periods in order to obtain more exact results.

6. Conclusions and Discussion

In this paper, we have analyzed two automated market making mechanisms with bounded losses, which allow for infinite liquidity in markets with few potential traders, which are usually to be found in company-internal markets. Both market mechanisms perform indistinguishably well in terms of forecasting accuracy. However, the dynamic pari-mutuel market is superior to the logarithmic scoring rules with respect to the losses which occur when operating a market. Specifically, when using the DPM, in short markets with only few trades, a mean subsidy of as low as 1.50 € is sufficient to provide liquidity, whereas the LMSR needs 3.66 € on average. Also, we found initial support that the amount of losses is roughly linear with respect to the number of trading periods. This amount of money can potentially be compared to the incentives which must be given to participants in order to encourage participation in play-money markets. Thus, depending on the area of application, it might even be less costly to subsidize a real-money market than to provide participants with high incentives.

Limitations of this study have to be attributed to its simulative nature. Mainly, it is not clear if traders behave equally expected-utility maximizing when exposed to different market mechanisms in reality. This might change the trading behavior and thus elicit deviations from the stylized market model. However, this should not have a significant impact on the general conclusions about the amounts of required subsidies found in this study.

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