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EVENT STUDIES IN REAL- AND PLAY-MONEY PREDICTION MARKETS

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Event study methodology is a powerful procedure to quantify the impact of events and managerial decisions such as new product announcements on the value of a publicly traded company. However, for many events, appropriate financial data may not be available, either because suitable securities are not traded on financial markets or confounding effects limit the insights from financial data. In such instances, prediction markets could potentially provide the necessary data for an event study. Prediction markets are electronic markets where participants can trade stocks whose prices reflect the outcome of future events, e.g. election outcomes, sports results, new product sales or internal project deadlines. One key distinction between different prediction market applications is whether they require real money investments or play-money investment with non-monetary incentives for traders. Thus, the goal of this paper is to compare prediction markets' ability to conduct event studies with respect to these two different incentive schemes. We empirically test the applicability of event study methodology in real-money vs. play-money prediction markets with two data sets. We show that event studies with prediction markets deliver robust and valid results with both incentive schemes.

Keywords: Prediction markets, event evaluation, decision making, event studies, play money vs. real money

1 INTRODUCTION

On the day of the iPhone announcement, the stock price of Apple soared 7% in 2006, while the stock of its competitor Research in Motion, the producer of Blackberry, slumped 6%. With such milestone events for publicly traded companies, the public assessment on managerial decisions is clearly reflected in the subsequent market reaction. One common approach to assess the impact of an event is to extract the very reaction caused by the event on the company's stock return. Analyzing stock market reactions helps to quantify the financial impact of company-specific or market-wide events on the company's market capitalization (MacKinlay 1997). Such information can provide a valuable retrospective assessment of managerial actions and serve as a prospective estimation for similar future events.

The basic idea behind market based evaluation of events is that the prices on a competitive market efficiently aggregate all (public) information available to the market participants (Fama 1970). Market efficiency implies that

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new information is subsequently incorporated in market returns, making the (financial) impact of that information quantifiable. Today, the so called event study methodology is widely accepted as a standard procedure to measure the impact of events with more than 500 papers published in leading journals since the 1970s (Kothari and Warner 2006). Examples of applications include the impact of new product introductions (c.f. Chaney et al. 1991), the timing of stock options awards to CEOs (Yermack 1997), mergers of firms (Rosen 2006) or even changes of a company's name (Horsky and Swyngedouw 1987).

In general, for the application of this rather clear-cut procedure, an appropriate security must be traded on an efficient financial market and the event must have a significant impact on the company's performance in order to induce a measurable effect on its stock returns. In cases where these prerequisites are not met, prediction markets (PMs), also referred to as virtual stock markets or information markets, can provide the required market data for such an analysis. PMs can model nearly any future forecasting goal as a virtual stock as long as its final date and its final outcome can be quantified (Spann and Skiera 2003). The forecasting goal of a virtual stock is very adaptable: it can refer to a vote share of a party or market share of a product, product units sold or success probabilities of different projects. Today, various PMs operate to predict the outcomes of political, financial, sports- or movie-related events, ranging from small-scale markets with as few as a dozen participants (Christiansen 2007) to more than one hundred thousand, as for example on the Hollywood Stock Exchange. Moreover, PMs can generally be relatively easily implemented. In business environments, various companies such as Google, Yahoo!, General Electric, Microsoft, Qualcomm or Eli Lilly have already applied company-internal PMs (e.g., Chen and Plott 2002; Ostrover 2005).

Although PMs employ the same market-based mechanism for information aggregation as financial markets, PMs differ from financial markets in several aspects concerning the stock price definition and stock's lifetime, and the amount of financial investment being traded (real- vs. play-money). The use of play-money vs. real-money as investment scheme in prediction markets has been debated with respect to participants' trading strategies (Gruca et al. 2003), incentives (Luckner and Weinhardt 2007) and forecasting accuracy (Servan-Schreiber et al. 2004). Real-money markets have closest resemblance to financial markets with the facet of real money being at stake. Moreover, different types of potentially less informed traders might participate in play-money markets. However, legal restrictions which prohibit the use of real-money markets and which exist for example in the United States may be an insuperable barrier for the use of real-money markets in certain circumstances. Therefore, when setting up markets with the aim of extending the PMs' field of application by using event study methodology, one key question is whether play-money suffices in general and if there are differences to real-money markets.

Thus, the objective of this paper is to test the applicability of the event study methodology for PMs with different investment schemes. We empirically test the performance of event study methodology in real- vs. play-money prediction markets based on two data sets of prediction markets for the same set of events using four evaluation criteria.

The remainder of the paper is organized as follows: Section 2 covers the basic idea and previous research on PMs. Section 3 describes the data and the event study design used for the analyses. The evaluation criteria and results are outlined in Section 4. The general discussion in Section 5 summarizes the findings and discusses areas of future research.

2 PREDICTION MARKETS

Idea and Theoretical Foundations of Prediction Markets

In PMs, outcomes of future events are modeled as virtual stocks, whilst the underlying payoff function determines the stocks' (terminal) values after a certain date. As on financial markets, a trader will sell an overvalued stock and buy an undervalued stock, according to his or her assessment of the stock's fair value and its comparison to the current market price. The assessment of the future value is dependent on the traders' opinions of the outcome of the stock's underlying event. Consequently, the price of a virtual stock reflects the aggregate expectations of all participants in case of an efficient market (Wolfers and Zitzewitz 2006). Thus, PMs can be used to derive predictions on the respective outcomes (Manski 2006). In almost two decades of research, the forecasts of PMs have been found to be generally at least as accurate compared to alternatives such as opinion polls or expert surveys (e.g. Forsythe et al. 1999; Spann and Skiera 2003).

In a PM, the remuneration of a participant is positively dependent on his predictive and trading performance, that is, his deposit value after the pay-off is determined based on the outcome of the events. Therefore, the results of a PM might be less biased towards personal preferences as the participants seek to maximize their deposit values (e.g., Spann and Skiera 2003). And, even though the majority of traders might be prone to make mistakes, a small group of "knowledgeable" participants will exploit such inefficiencies and set efficient prices (Forsythe et al. 1999; Oliven and Rietz 2004). Some PMs require rather small (such as the Iowa Electronic Markets) or even permit significant (the first PM in this study) real-money investments, but also play-money markets as the Hollywood Stock Exchange, NewsFutures and IdeaFutures have independently shown to perform well, regarding point-predictions on specific dates (Pennock et al. 2000; Servan-Schreiber et al. 2004; Spann and Skiera 2003).

A great scope of versatile design options concerning forecasting goal, different number of participants, and market structures exist among various PMs. In general, the design of a PM has to be carefully calibrated to the type of forecasting goal and the setting of the market (e.g., Spann and Skiera 2003).

One of the main design options is the choice of the payoff function. Generally, the (terminal) value (payoff) of a virtual stock after a certain event date T, that is, the (play-) money each stock owner receives after the event occurs, is dependent on the true value of the outcome that is transferred via the payoff function ϕ:

(1) $d_i = \phi(Z_i)$, $i \in I$

where

d_i = payoff of virtual stock *i*,
$\phi(\cdot)$ = payoff function,
Z_i = actual outcome of stock *i*'s forecasting goal at time *T*,
I = index set of stocks.

Other design options are the market mechanism, different incentive schemes (Luckner and Weinhardt 2007) and the duration of the prediction market. For respective taxonomies see Spann and Skiera (2003) and Wolfers and Zitzewitz (2004).

Previous Research on Continuous Reactions of Prediction Market Prices to Events and Comparisons of Play- and Real-Money Markets

The majority of previous research focused on the forecast accuracy of PMs compared with alternative forecasting methods at one specific point in time, i.e., the final prediction, rather than on the development of prices over time. For a detailed overview of the current research and studies see Tziralis and Tatsiopoulos (2007).

Few studies analyze the continuous reactions of prices on prediction markets to events: Berg and Rietz (2003) propose to use PMs along with conditional PMs as decision support systems by analyzing the correlation of different stocks over time. Pennock et al. (2002) develop a model of how new information is incorporated into market prices and test an algorithm for automatically detecting and explaining events with external datasources such as Usenet. Wolfers and Zitzewitz (2008) and Snowberg et al. (2007) extract additional, otherwise "oblique", information from financial markets data with the help of PMs. They suggest that PMs can help to understand the movements of financial markets by incorporating ex-ante expectations and as a result, for example, being able to quantify the monetary value of political actions or major events during an election.

Elberse (2007) conducts a classic event study procedure with the data provided by Hollywood Stock Exchange on a daily data basis. Borghesi (2006) applies the event study methodology with minute-wise data to analyze a real-money market where he detects that market participants underreact to new information. In a recent study, Easton and Uylangco (2007) analyze a real-money cricket betting market and find rapid information incorporation as a result of news and a high predictive validity of odds. However, the investigated market is not a virtual stock market as such, where stocks can be bought and sold, but relies on odds which traders set.

No study that we are aware of has compared the performance of real-money markets and play-money markets concerning continuous reaction to events. One of the two known studies to date which compare play-money market with real-money markets focuses on forecast accuracy with an analysis of NFL (American football league) game markets and finds no significant difference between the forecast accuracy of either market (Servan-Schreiber et al. 2004). Rosenbloom and Notz (2006) find that in non-sports events, real-money markets are more accurate than play-money markets. However, for sports-events, they are comparably accurate. Additionally, a new study (Luckner and Weinhardt 2007) has compared the effect of different incentive schemes on the predictive accuracy of PMs, where the authors show that, surprisingly, a rank-order tournament leads to better prediction results than a performance-related incentive scheme.

3 GOAL AND DESIGN OF EMPIRICAL STUDY

Goal of the Study

The analysis of previous research on prediction markets revealed that the applicability of the event study methodology in prediction markets with real-money vs. play-money investments has not been compared yet. However, this design consideration may be critical for the ability of a PM to provide data for event studies, especially for short-horizon events. Therefore, we want to test the performance of the event study methodology in prediction markets with both investment schemes.

Data and Requirements

For the goal of our study, we choose a data set which includes two prediction markets (play and real money) for the same set of events. Further, this data set had to include a sufficient number of events for our analysis. Finally and most importantly, the data should meet the requirements for the application of event study methodology (McWilliams and Siegel 1997):

(a) The market is (semi-strong) efficient with all publicly available information being reflected in the stock prices.
(b) No confounding effects which might have an influence on stock returns occur in the estimation or event windows.
(c) Events must be unanticipated since otherwise, they are already incorporated in stock returns in case of market efficiency.

We chose to use data from two major sports PMs conducted during the 2004 European soccer championship. The European soccer tournament lasted three weeks in June 2004 with 16 teams playing 31 games. The first three games for each team were played in group games (overall 4 groups) to qualify for the quarter finals, where the knock-out rounds started. The event study is conducted during the games, which is the time period when the major events occur.

For the requirements of an event study, we conclude that the existence of market efficiency (a) cannot be determined prior to conducting the event study. However, the market data and events to be analyzed can be selected in advance according to requirements (b) and (c). In this case, sports (soccer) market data serves as ideal basis for this research and has been used in a number of previous studies (e.g., Rosenbloom and Notz 2006; Luckner and Weinhardt 2007; Servan-Schreiber et al. 2004). First, during soccer games, no confounding effects exist that could add unwanted noise (requirement (b)). Events which are subject to possible confounding effect can be excluded from the study if all relevant event data is present (which is the case for our data sets). Then, because of fast actions and sudden incidences in soccer games, events can hardly be anticipated (requirement (c)). Moreover, as a consequence of the decisive events clustered in ninety minutes of the game, the trading volume during the game is exceedingly high compared to non-playing time, allowing for a fine-grained intra-game analysis.

Prediction Market Design

Both PMs were operated and developed by professional firms. The real-money PM1 was operated by a major German betting company for sport and finance related events. The play-money PM2 was conducted as an online competition for a major online broker, also offered by a firm specialized in online games and contests. Both web-based user interfaces offered rich information on the teams, the stock history and the respective events, as well as dynamic price charts and the best five open bid and ask orders. Both PMs' employed a continuous double auction as market mechanism, which is the common mechanism used in financial markets. See Table 1 for an overview of the two prediction markets.

Prediction Market 1 (PM1): Real-Money Market

In PM1 three kinds of winner-takes-all stocks existed for each game: two for the cases team A or team B wins, and one if there was a draw, which was defined as the case when the scores were equal after the regular playing time. The winning stock was valued at 10€, the remaining two stocks at 0 €:

$$d^{PM1}_{i,A/B/Draw} = \begin{cases} 10\text{ €, if Team A wins / Team B wins / Draw in i-th game} \\ 0\text{ €, otherwise} \end{cases} \tag{2}$$

Thus, the price of a virtual stock at a given point in time (divided by 10) can be interpreted as the likelihood for the corresponding event to occur (Wolfers and Zitzewitz 2006).

The participants could trade virtual stocks as long as they had a sufficient amount of money in their cash deposit to buy (no short positions were al-

TABLE 1
OVERVIEW OF PREDICTION MARKETS IN DATA SETS

	PM1	PM2
Forecasting goal	outcome of one game	final standing of a team in the tournament
Investment type	real-money investment	play-money
Initial endowment	no initial endowment	100 stocks per team + 30,000 monetary units
No. of markets	31 (one per game)	1 (during tournament)
No. of stocks	3 per game (Team A wins / Team B wins / draw after the regular playing time)	16 (one for each team)
Payoff function	winner-takes-all	multi-part step
Trading mechanism	continuous double auction	continuous double auction
No. of registered traders	6,569	9,077

lowed) or sufficient stocks in their portfolio to sell. In addition, the provider charged a 2% commission fee for each trade.

Prediction Market 2 (PM2): Play-Money Market

In PM2, the goal was to predict the final standings of the team, which was reflected in the multi-part payoff function (MU: monetary units) of virtual currency that did not correspond to any real-world currency:

$$d_i^{PM2} = \begin{cases} 300\text{ MU, if team} & i \text{ becomes champion,} \\ 200\text{ MU, if team} & i \text{ becomes vice-champion,} \\ 150\text{ MU, if team} & i \text{ is eliminated in the semi-finals,} \\ 100\text{ MU, if team} & i \text{ is eliminated in the quarter finals,} \\ 75\text{ MU, if team} & i \text{ becomes third in group games,} \\ 50\text{ MU, if team} & i \text{ becomes fourth in group games.} \end{cases}, \text{ with } i \in \{1, \ldots, 16\} \tag{3}$$

The traders were incentivized by the possibility to win prizes, which were given to top performers.

Event Study Design

Event Data Collection

The data on events was retrieved from the official UEFA (Union of European Soccer Associations) database. In total, over 400 events were collected, including minor events as yellow cards or player substitutions. The exact times have additionally been double checked with minute-by-minute game descriptions of three data sources: the major German sports newspaper "Kicker", the

German sports internet portal “Sport1”, and the “BBC” online sports section. We only take goals into consideration since they have the most decisive impact on the game and tournament outcomes and thus on stock returns compared to other events such as yellow/red cards or player substitutions.

Moreover, we focus on the total set of 77 goals. Goals from penalty shots were excluded since the penalty shots' outcomes could be anticipated with the referee decision (violating the 3rd prerequisite). For example, 75 % of penalty shots are turned into goals in Italian and French soccer (Chiappori et al. 2002). Additionally, goals in overtime were excluded because PM1 predicted only the outcome after the regular playing time. We set the estimation and event period to 7 and 4 minutes, respectively, based on the tradeoff between availability of data for model estimation and availability of events. To avoid confounding events, we omitted those goals which were preceded by events (including events with low impact such as yellow cards) during the estimation period or which were succeeded by other events during the event period. In addition, the events in concurrent games of the same group in the last games of the preliminary round were also excluded. Moreover, trading data was not present for a few sections of games, apparently due to server downtime. This leaves a total of 42 goals to be analyzed for both PM1 and PM2.

Expected Return Model

In event study literature, basically two types of models to determine expected returns exist (for overviews see Binder 1998; Kothari and Warner 2006; MacKinlay 1997; McKenzie et al. 2004). *Non-market based models* do not include return correlation with other stocks while *market-based models* also consider correlation with other stocks' returns (see the Appendix for the standard procedure of the event study methodology). In financial markets, usually market-based models (e.g. Kothari and Warner 2006) are applied to determine expected returns in the event window in order to account for overall market or index movements non-conditional on the particular event affecting only one stock's returns. However, in case of PM1 and PM2 in this study, single stocks' prices, and thus, returns, in a market are negatively correlated. For example, in PM1, a winner-takes-all payoff function is used, implying that in case of market efficiency, all prices of stocks sum up to a given, predetermined amount. Thus, we have

$$c = \sum_{i \in I} p_{i,t} = p_{j,t} + \sum_{i \in I, i \neq j} p_{i,t} = \underbrace{(p_{j,t} + \delta)}_{p_{j,t+1}} + \underbrace{\left(\sum_{i \in I, i \neq j} p_{i,t} - \delta \right)}_{\sum_{i \in I, \imath \neq j} p_{i,t+1}} = c \tag{4}$$

showing the negative correlation of stock prices (and implicitly, stock returns). Ultimately, an appropriate index cannot be created and only non-market based models can be applied. A similar rationale applies for PM2.

Thus, for both PMs, we use the (non-market) constant mean return model (CMR) (MacKinlay 1997).

We test the significance of the aggregated abnormal returns (AAR) for a certain period t by using the t-statistic from Brown and Warner (1985), which is $\lambda_t^{AAR} = \frac{AAR_t}{SD(\overline{AAR})} \sim N(0,1)$. $SD(\overline{AAR})$ is the standard deviation of the mean of aggregated abnormal returns in the estimation window.

We test the significance of the cumulative aggregated abnormal returns (CAARs) with the t-statistic described in Kothari & Warner (2006), which is $\lambda_t^{CAAR} = \frac{CAAR_t}{\sqrt{L * \text{var}(\overline{AAR})}} = \frac{CAAR_t}{\sqrt{L} * SD(\overline{AAR})}$, where $L = |t - t_1 + 1|$.

Although we have a lower number of transactions in PM1 than in PM2 (see Table 1), we choose to set the length of a period t to 20 seconds for both markets since an extension to 30 seconds would not have decreased the number of missing values substantially. For both PMs, we use the last price reported during the period of 20 seconds. In case of missing values in a specific period, the last transaction price is used. In order to achieve an easy interpretability of returns, we compute relative returns instead of log returns.

4 RESULTS OF EMPIRICAL STUDY

Evaluation Criteria

We investigate the applicability of event study methodology for both incentive schemes based on the following criteria, which reflect the degree of market efficiency and the stability of the event study results:

1. *Magnitude and stability of the stock price reaction and stability of returns.* We conduct an event study for all events and stocks with different types of goals and measure the reaction to events which is reflected in the AARs and the CAARs.
2. *Speed of information incorporation.* Significant abnormal returns in the event window indicate if new information is incorporated in the market. Therefore, we calculate the number of periods in which the AARs are significant during the event window for each event and stock independently and quantify how fast the new information is reflected in stock prices. The speed of information incorporation is lower if more periods with significant AARs are observed.
3. *Change of predictive accuracy.* We compute the absolute error (AE) of the predictive accuracy before and after the event to obtain possible improvement rates as a consequence of market reactions to events.
4. *Liquidity.* We compare both PMs with respect to their liquidity by various measures.

Evaluation Results

Magnitude of Stock Price Reactions and Stability of Returns

The results of the event study with all 42 events are displayed in Table 2, Table 3 and Figure 1.

In PM1, the AARs are significant ($p < 0.01$) from the 100-second to the 60-second period for goals (except in the 40-second period) and remain insignificant thereafter. The highest impact with a high t-value of 29.66 can be observed for the 40-second period. The CAARs remain significant ($p < 0.01$) from the first significant reaction of the AARs on.

For goals against, AARs show a significant reaction ($p < 0.01$) from the 60-second period on, in conjunction with the reaction of the CAARs in this period. The CAARs remain significant, while the AARs become insignificant from the 60-second period on. The difference of the timing of significant periods indicates that participants first trade the stock of the scoring team and subsequently the stocks of the other team. Comparing the magnitude of reactions, goals, with a CAAR of 115.45 at the end of the event window (120-seconds period), have a considerably larger impact than goals against (CAAR = –47.69), meaning that on average goals add 115 % value to the corresponding stock, while goals against take about 48 % off the respective stocks' values. The case for the draw stocks is less clear. As it can be inferred from Figure 1, CAARs first increase and then decrease again. AARs significantly rise in the 100-/-80-/-40-seconds periods and fall in the 0-/40-/80-seconds periods. CAARs are only significant from the 80- until the 100-second period.

In PM2 (Table 3), the first significant reaction in case of goals of the AARs can be observed in the 60-seconds period, staying significant until the 40-seconds period (where $p < 0.01$). The 120-seconds period has a significant AAR as well, however, the t-values of –3.27 is considerably lower than those of the significant AARs before. The CAARs are consistently significant from the 40-seconds period on.

In case of negative events (i.e. goals against) we can observe a significant reaction of the AARs from the 60-seconds period on for five more periods. The CAARs are significant from the 0-seconds period on. A correction of returns seems to take place in the 120-seconds period, where the AAR is positive.

In PM2, the magnitude of average reaction is considerably larger for goals against (–5.45%) compared to the average reaction to goals (2.75%).

The difference in the magnitude of reaction to goals of each PM is explained by the different horizons of the forecasting goal and the payoff function itself. Thus, since the real-money prediction market (PM1) traded three stocks that reflected each possible outcome of a single game, the price reaction to events is of higher magnitude than in the play-money market (PM2), where stocks reflected the overall tournament performance of a team. Therefore, the prices of a stock in PM2 potentially include the outcome of several games.

TABLE 2
(CUMULATIVE) AVERAGE ABNORMAL RETURNS OF PM1

	Goal				Goal Against				Draw			
sec.	AAR	t	CAAR	t	AAR	t	CAAR	t	AAR	t	CAAR	t
–320	–1.30	–1.58	–1.72	–0.66	–1.00	–0.90	1.36	0.39	0.46	0.85	0.20	0.12
–300	–0.07	–0.09	–1.81	–0.74	–0.68	–0.62	0.68	0.20	0.10	0.18	0.30	0.18
–280	1.91	2.33**	0.52	0.22	1.50	1.35	2.17	0.69	–0.55	–1.00	–0.25	–0.16
–260	–0.27	–0.33	0.18	0.08	–0.85	–0.76	1.33	0.45	0.30	0.55	0.05	0.04
–240	0.19	0.24	0.42	0.21	0.96	0.86	2.29	0.84	0.30	0.55	0.35	0.26
–220	0.00	0.00	0.42	0.23	–0.52	–0.47	1.77	0.71	0.21	0.38	0.56	0.46
–200	–1.22	–1.49	–1.06	–0.65	–1.35	–1.22	0.42	0.19	0.15	0.28	0.71	0.65
–180	0.00	0.00	–1.07	–0.75	0.04	0.03	0.45	0.23	–0.33	–0.60	0.38	0.40
–160	0.41	0.50	–0.57	–0.49	–0.30	–0.27	0.15	0.10	0.43	0.78	0.81	1.05
–140	–0.21	–0.25	–0.82	–1.00	–0.24	–0.22	–0.09	–0.08	–0.66	–1.20	0.15	0.28
–120	0.67	0.82	0.00	0.00	0.09	0.08	0.00	0.00	–0.15	–0.28	0.00	0.00
–100	3.30	4.03***	4.03	4.91***	–2.38	–2.14**	–2.38	–2.14**	3.18	5.83***	5.83	10.66***
–80	12.30	15.01***	19.04	16.42***	–1.71	–1.54	–4.09	–2.60**	4.88	8.92***	14.75	19.08***
–60	7.55	9.21***	28.24	19.89***	–4.07	–3.67***	–8.17	–4.24***	–1.10	–2.01*	12.74	13.46***
–40	24.31	29.66***	57.91	35.32***	–8.96	–8.06***	–17.13	–7.71***	6.30	11.53***	24.27	22.20***
–20	18.64	22.74***	80.64	44.00***	–11.61	–10.45***	–28.74	–11.57***	–0.43	–0.78	23.49	19.22***
0	11.57	14.11***	94.75	47.20***	–16.51	–14.86***	–45.25	–16.62***	–4.49	–8.22***	15.27	11.41***
20	10.34	12.61***	107.37	49.51***	–3.62	–3.26***	–48.88	–16.62***	–0.58	–1.06	14.21	9.83***
40	–1.13	–1.38	105.99	45.72***	–3.39	–3.05***	–52.27	–16.63***	–2.59	–4.74***	9.47	6.13***
60	6.14	7.49***	113.48	46.15***	–0.30	–0.27	–52.57	–15.77***	0.22	0.41	9.88	6.03***
80	0.86	1.05	114.54	44.19***	2.89	2.60**	–49.67	–14.13***	–1.94	–3.55***	6.33	3.66***
100	1.21	1.47	116.01	42.68***	1.53	1.38	–48.14	–13.06***	–1.47	–2.69**	3.65	2.01*
120	–0.46	–0.56	115.45	40.66***	0.45	0.41	–47.69	–12.39***	0.21	0.39	4.04	2.13**

(n.s.: not significant, *: $p < 0.1$, **: $p < 0.05$, ***: $p < 0.01$)

TABLE 3
(CUMULATIVE) AVERAGE ABNORMAL RETURNS OF PM2

	Goal				Goal Against			
sec.	AAR	t	CAAR	t	AAR	t	CAAR	t
–320	0.01	0.24	0.09	0.63	–0.06	–0.78	–0.03	–0.11
–300	0.00	–0.06	0.09	0.65	0.02	0.33	–0.08	–0.38
–280	–0.05	–0.98	0.04	0.34	0.12	1.58	–0.06	–0.28
–260	0.00	–0.06	0.04	0.34	0.08	1.05	0.06	0.30
–240	–0.04	–0.85	0.00	0.02	–0.08	–1.14	0.13	0.75
–220	0.04	0.79	0.04	0.38	–0.11	–1.47	0.05	0.31
–200	0.02	0.41	0.06	0.63	0.11	1.53	–0.06	–0.39
–180	0.01	0.26	0.07	0.88	–0.04	–0.48	0.06	0.44
–160	–0.01	–0.11	0.06	1.00	0.02	0.30	0.02	0.20
–140	–0.01	–0.21	0.06	1.20	–0.04	–0.58	0.04	0.58
–120	–0.06	–1.20	0.00	- -	–0.08	–1.05	0.00	- -
–100	–0.06	–1.21	–0.06	–1.21	–0.02	–0.27	–0.08	–1.05
–80	–0.02	–0.39	–0.07	–1.13	0.06	0.82	–0.10	–0.93
–60	0.16	3.48***	0.09	1.09	–0.44	–5.98***	–0.04	–0.29
–40	0.62	13.51***	0.71	7.70***	–0.38	–5.23***	–0.47	–3.24***
–20	0.13	2.94***	0.84	8.20***	–1.47	–20.04***	–0.86	–5.24***
0	0.27	5.97***	1.12	9.92***	–1.65	–22.52***	–2.32	–12.96***
20	0.92	20.01***	2.04	16.75***	–0.75	–10.28***	–3.97	–20.51***
40	0.74	16.13***	2.78	21.37***	–0.09	–1.22	–4.72	–22.82***
60	–0.10	–2.16**	2.68	19.43***	–0.63	–8.68***	–4.81	–21.92***
80	–0.05	–0.98	2.63	18.12***	0.09	1.20	–5.44	–23.54***
100	–0.03	–0.69	2.60	17.07***	–0.10	–1.31	–5.36	–22.09***
120	0.15	3.27***	2.75	17.28***	0.31	4.28***	–5.45	–21.52***

(n.s.: not significant, *: p < 0.1, **: p < 0.05, ***: p < 0.01)

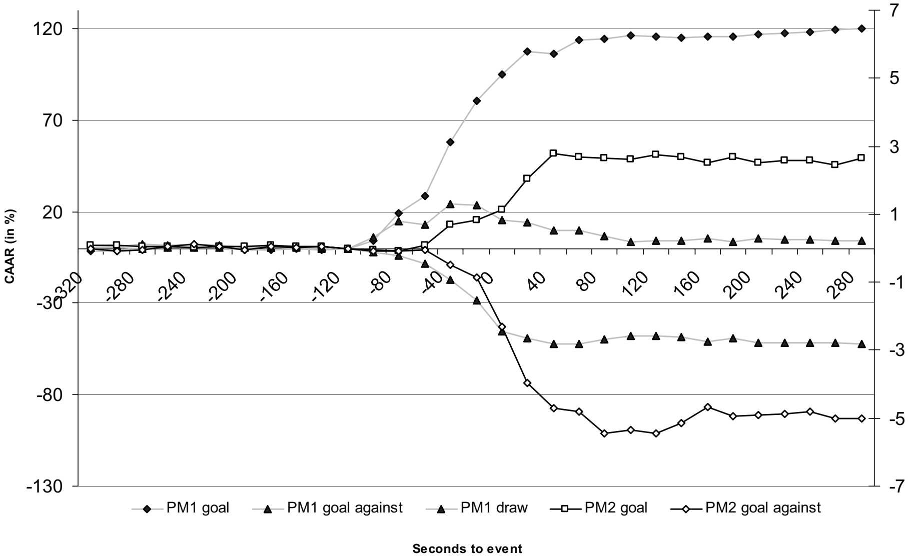

FIGURE 1. Cumulative average abnormal returns of PM1 (left scale) and PM2 (right scale).

Speed of Information Incorporation

To compare the speed of information incorporation, we calculate the number of periods with significant AAR (at the 5% level) for each stock and each event i and type r (goal, goal against, [draw]) in the event window, which consists of 12 periods of 20 seconds each:

$$\text{(5)} \qquad \text{No. of periods with significant AAR in Event Window}_{i,r} = \sum_{t^* \in T^*} \delta_{i,r,t^*}$$

where

$$\text{(6)} \qquad \delta_{i,r,t^*} = \left\{ \begin{array}{l} 1, \text{ if } |\lambda_{t^*}^{AAR}| > \, tinv(.05) \text{ of event } i \text{ and stock type } r \\ 0, \text{ otherwise.} \end{array} \right\}$$

and $T^* = \{-100, -80,\ldots,120\}$. Therefore, we assume that the information incorporation has ended with the 120-seconds period.

For PM1, the average number of periods with significant AARs is similar for all three types of payoffs, ranging from 3.37 (goal against) to 3.42 (goal and draw) out of 12 periods in the event window (Table 4). However, the standard deviation of slightly more than 2 indicates a rather high variation. On average, PM1 incorporates the new information within 1 minute and 8 seconds (3.4 periods).

In PM2, the range between the types of stocks is greater: 4.86 (sd = 2.26) periods for goals compared to 3.31 periods (sd = 2.27) for goals against, indicating a faster reaction to goals against than to goals (Table 4). Accordingly, the average speed of information incorporation here is 1 minute and 22 seconds.

Thus, on average, the time of information incorporation in PM1 is 14 seconds longer than in PM1, which is significant at the 5%-level (two-sided t-test).

Change of Predictive Accuracy

We use the absolute error (AE) measure to analyze the predictive accuracy of both PMs. We calculate the AE of the stocks corresponding to event i

TABLE 4
SPEED OF INFORMATION INCORPORATION

	Avg. no. of periods with significant AAR in Event Window (SD) in PM1		Avg. no. of periods with significant AAR in Event Window (SD) in PM2	
	Periods	Seconds	Periods	Seconds
Goal	3.42 (2.25)	68.4 (45.0)	4.86 (2.26)	97.2 (45.2)
Goal against	3.37 (2.10)	67.4 (42.0)	3.31 (2.27)	66.2 (45.4)
Draw	3.42 (2.30)	68.4 (46.0)	-	-
Total	3.40 (2.20)	68.0 (44.0)	4.08 (2.38)	81.6 (47.6)

and type r (goal, goal against, (draw)) in the last estimation period t^{before} and in the last event period t^{after}. The error of a stock is the absolute deviation of its price $p_{i,r,t^{before(after)}}$ and its final payoff $d_{i,r}$:

$$(7) \qquad AE_{i,r}^{before(after)} = \left| p_{i,r,t^{before(after)}} - d_{i,r} \right|$$

In both PMs, adjustments of prices in reaction to events lead to a higher predictive accuracy, implying an efficient reaction of the markets (Table 5). The magnitude of the total improvement of PM1 (16.24%) is larger than the improvement for PM2 (5.09%), while both improvement rates are significant. This effect, again, can be attributed to the different payoff functions and durations of both PMs. However, the improvement rates for goals against compared to the remaining two (one) type(s) are considerably larger in both PMs. In PM1, the goal stocks' improvement is 4.72% and not significant. In PM2, the improvement of goals stocks is only 1.40% and again not significant.

Thus, both markets improve their predictive accuracy as a reaction to new events (although not significantly in case of goals, but with the correct sign), while they both assess the negative events in a more accurate way.

Liquidity

While in the real- vs. play-money studies (Rosenbloom and Notz 2006; Servan-Schreiber et al. 2004), no statements about the markets' properties

TABLE 5
CHANGE OF PREDICTIVE ACCURACY

	Mean AE before event (sd)	Mean AE after event (sd)	Mean relative improvement
PM1			
Goal	4.40	4.19	4.72 % n.s.
	(2.90)	(2.81)	
Goal against	4.03	2.61	35.02 % ***
	(2.61)	(2.71)	
Draw	4.22	3.53	13.49 % **
	(2.39)	(2.55)	
Total	4.21	3.44	16.24 % ***
	(2.63)	(2.75)	
PM2			
Goal	50.73	50.02	1.40 % n.s.
	(45.35)	(43.76)	
Goal against	45.61	41.43	9.16 % ***
	(38.53)	(39.84)	
Total	48.17	45.72	5.09 % ***
	(41.90)	(41.76)	

(n.s.: not significant, *: $p < 0.1$, **: $p < 0.05$, ***: $p < 0.01$)

TABLE 6
LIQUIDITY IN MARKETS

	PM 1	PM 2	Rel. difference
General liquidity in market			
Total no. of trades during games	45,662	112,364	146.07 % ***
Avg. no. of traders per game (sd)	454	906	99.82 % ***
	(108)	(244)	
Avg. no. of trades per game (sd)	1,473	3,625	146.07 % ***
	(1,131)	(480)	
Avg. no. of trades per game per trader (sd)	3.18	3.99	25.74 % ***
	(0.49)	(0.68)	
Avg. no. of trades per game per stock (sd)	491	1,812	269.12 % ***
	(160)	(566)	

(n.s.: not significant, *: $p < 0.1$, **: $p < 0.05$, ***: $p < 0.01$)

in terms of liquidity were made, it is especially important to observe liquidity when analyzing continuous price reactions. Although no causal statement can be made about the applicability of event studies with respect to liquidity without a controlled experiment, some descriptive statistics are presented to show the amount of liquidity in PM1 and PM2, where the event studies have shown good results.

The number of traders (454 (sd = 108) in PM1 compared to 906 (sd = 244) in PM2, Table 6) and the number of trades (1,473 (sd = 1,131) in PM1 and 3,625 (sd = 480) in PM2) was significantly lower in PM1. Also, the number of trades per trader and game was significantly lower in PM1 (3.18 (sd = 0.49) trades compared to 3.99 trades (sd = 0.68)). The lower number of trades per trader in PM1 is likely to be attributed to a trading fee of 2% per trade which was charged and which might have prevented participants from trading more frequently.

Moreover, with only two stocks which were traded in PM2 per game compared to three in PM1, on average the number of trades in PM1 per stock was 491 compared to 1,812 in PM2.

Thus, considering the indicators of overall and event specific liquidity, it can be inferred that PM1 is less liquid than PM2. Although we cannot draw causal conclusions about the dependence of liquidity on the applicability of event studies in these PMs, the previous analyses indicate that the given liquidity (see Table 6) enabled these markets to perform well.

5 GENERAL DISCUSSION

The primary motivation for the application of event studies with data from PMs is the broad range of forecasting applications because they can a) be set up for nearly any future event and b) are less prone to confounding effects due to the flexible forecasting goal.

In this paper, we showed that event study methodology can be applied to PMs with both, play- and real-money investments. Our results show that information is incorporated into stock returns in less than 90 seconds on average in both PMs, however, more slowly in play-money markets. An application of the event study methodology revealed stable and clear reactions to events in both cases, which most likely was also the consequence of the identification and removal of confounding effects. A validation of reactions to events by comparison of the forecast error showed that in both markets, the predictive accuracy increased as consequence of the event reaction, implying an efficient market reaction on average.

Thus, we yield comparably good results for both PMs for the same events regardless of the payoff function and monetary investment scheme, which is an important aspect when setting up PMs or using PMs for event studies. One possible reason why play-money markets performed comparably well as real-money markets was identified by the fact that the play-money PM was considerably more liquid in terms of frequency of trading, number of participants and trading before and after events. With high liquidity, potential uninformed trading in play-money markets (Gruca et al. 2003) can quickly be adjusted by more informed traders. On the other hand, due to the potential absence of uninformed trading, even lower-liquidity real-money markets can also perform well. Hence, we conclude that both, play-money PMs with sufficient liquidity and real-money PMs can provide the necessary data for event studies.

However, our study faces some limitations since our data sets differed with respect to stock payoffs and liquidity. Based on these limitations, future research should experimentally test the performance of event study methodology in play-money vs. real-money prediction market under tightly controlled laboratory conditions where comparable liquidity is ensured. Further, the extension of event study methodology to company internal prediction markets with low liquidity or a smaller number of participants is a promising area for future research.

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REFERENCES

J E Berg and T A Rietz ‘Prediction markets as decision support systems’ *Information Systems Frontiers* (2003) 5(1) 79–93.

J L Binder ‘The event study methodology since 1969’ *Review of Quantitative Finance and Accounting* (1998) 11 111–37.

R Borghesi ‘Underreaction to new information: Evidence from an online exchange’ Working Paper (2006) Texas State University.

S J Brown and J B Warner 'Using daily stock returns - The case of event studies' *Journal of Financial Economics* (1985) 14 3–31.

P K Chaney, T M Devinney and R Winer 'The impact of new product introductions on the market value of firms' *Journal of Business* (1991) 64(4) 573–610.

K-Y Chen and C R Plott 'Information aggregation mechanisms: Concept, design and implementation for a sales forecasting problem' Working Paper (2002) California Institute of Technology.

P-A Chiappori, S Levitt and T Groseclose 'Testing mixed-strategy equilibria when players are heterogeneous: the case of penalty kicks in soccer' *American Economic Review* (2002) 92(4) 1138–51.

J D Christiansen 'Prediction markets; Practical experiments in small markets and behaviours observed' *Journal of Prediction Markets* (2007) 1(1) 17–41.

S Easton and K Uylangco 'An examination of in-play sports betting using one-day cricket matches' *Journal of Prediction Markets* (2007) 1(2) 93–109.

A Elberse 'The power of stars: Do star actors drive the success of movies?' *Journal of Marketing* (2007) 71(4).

E F Fama 'Efficient capital markets: A review of theory and empirical work' *Journal of Finance* (1970) 25 383–417.

R Forsythe, T A Rietz and T W Ross 'Wishes, expectations and actions: A survey on price formation in election stock markets' *Journal of Economic Behavior & Organization* (1999) 39 83–110.

T S Gruca, J Berg and M Cipriano 'The effect of electronic markets on forecasts of new product success' *Information Systems Frontiers* (2003) 5(1) 95–105.

D Horsky and P Swyngedouw 'Does it pay to change your company's name? A stock market perspective' *Marketing Science* (1987) 6(4) 320–35.

S P Kothari and J B Warner 'Econometrics of event studies' in B Espen Eckbo (ed) *Handbook of Corporate Finance: Empirical Corporate Finance Vol. A* (North Holland, Elsevier, 2006).

S Luckner and C Weinhardt 'How to pay traders in information markets? Results from a field experiment' *Journal of Prediction Markets* (2007) 1(2) 1–10.

C M MacKinlay 'Event studies in economics and finance' *Journal of Ecomomic Literature* (1997) 35(3) 13–39.

C F Manski 'Interpreting the predictions of prediction markets' *Economic Letters* (2006) 91(3) 435–29.

A M McKenzie, M R Thomsen and B L Dixon 'The performance of event study approaches using daily commodity futures returns' *Journal of Futures Markets* (2004) 24(6) 533–55.

A McWilliams and D Siegel 'Event studies in management research: Theoretical and empirical issues' *Academy of Management Journal* (1997) 40(3) 626–57.

K Oliven and T A Rietz 'Suckers are born but markets are made: Individual rationality, arbitrage, and market efficiency on an electronic futures market' *Management Science* (2004) 50(3) 336–51.

S Ostrover 'Employing Information markets to achieve truly colloborative sales forecasting' *Journal of Business Forecasting* (2005) 24(1) 9–12.

D M Pennock, S Debnath, E J Glover and C L Giles 'Modeling information incorporation in markets, with application to detecting and explaining events' in Adnan Darwiche and Nir Friedman (eds). Proceedings of the 18th Conference on Uncertainty in Artificial Intelligence (San Francisco, Morgan Kaufman Publishers, 2002).

D M Pennock, S Lawrence, L C Giles and F A Nielsen *The Power of Play: Efficiency and Forecast Accuracy in Web Market Games* (Princeton, NEC Research Institute, 2000).

R J Rosen 'Merger momentum and investor sentiment: The stock market reaction to merger announcements' *Journal of Business* (2006) 79 987–1017.

E S Rosenbloom and W W Notz 'Statistical tests of real-money versus play-money prediction markets' *Electronic Markets* (2006) 16(1) 63–69.

E Servan-Schreiber, J Wolfers, D M Pennock and B Galebach 'Prediction markets: Does money matter?' *Electronic Markets* (2004) 14(3) 243–51.

E Snowberg, J Wolfers and E Zitzewitz 'Partisan impacts on the economy: Evidence from prediction markets and close elections' *Quarterly Journal of Economics* (2007) 122(2) 807–829.

M Spann and B Skiera 'Internet-based virtual stock markets for business forecasting' *Management Science* (2003) 49(10) 1310–26.

G Tziralis and I Tatsiopoulos 'Prediction markets: An extended literature review' *Journal of Prediction Markets* (2007) 1(1) 75–91.

J Wolfers and E Zitzewitz 'Interpreting prediction market prices as probabilities' Working Paper (2006) University of Pennsylvania and Stanford University.

---- 'Prediction markets' *Journal of Economic Perspectives* (2004) 18(2) 107–26.

---- 'Using marketing to evaluate policy: The case of the Iraq War' *Economica* (2008) forthcoming.

D Yermack 'Good timing: CEO stock option awards and company news announcements' *Journal of Finance* (1997) 52(2) 449–76.

APPENDIX: STANDARD PROCEDURE OF EVENT STUDIES

When measuring the effect of an event on the stock return, the *abnormal return* (AR) of a stock that was potentially caused by the event has to be determined. Therefore, an expected return of the stock in case the event did not occur is subtracted from the actual return R_{it} of the stock i in time t:

$$(8) \qquad AR_{i,t} = R_{i,t} - E(R_{i,t}|X_t)$$

While R_{it} is the actual observable return, different models have been proposed of how to determine the expected return, $E(R_{it}|X_t)$with X_t being the required market data up to period t. The parameters to estimate the expected return are determined in an *estimation window* with the corresponding return model, ranging from $t = T_0 + 1$ to, $t = T_1$, with $t = 0$ as the event date. The *event window*, $t = T_1 + 1$ to $t = T_2$, is used to estimate the price of the stock during the occurrence of the event. Due to the event date uncertainty and the possibility that some information might have leaked to the market earlier, the event window usually starts before $t = 0$.

As abnormal returns are observed over a set of stocks (or over several points in time), abnormal returns are aggregated for each period to obtain the joint abnormal return (*cross-sectional aggregation)*, leading to *average abnormal returns*:

$$(9) \qquad AAR_t = \frac{1}{N}\sum_{i=1}^{N} AR_{i,t}$$

The expected standard deviation can be calculated using methods as found in Brown and Warner (1985) or MacKinlay (1997).

Subsequently, in order to account for a multiple period event window and to capture all effects, abnormal returns are aggregated, resulting in *cumulated average abnormal returns*:

$$(10) \qquad CAAR(t_1, t_2) = \sum_{t=t_1}^{t=t_2} AAR_t$$

Finally, a two-sided test of the null hypothesis is applied using a standard statistic (Kothari and Warner 2006) dividing the (C)AAR by their standard deviation, analyzing whether the returns from the estimation window have significantly changed in the event window both for cumulated or non-cumulated returns:

$$H_0 : E(AAR) = 0 \leftrightarrow H_1 : E(AAR) \neq 0 \text{ and}$$
$$H_0 : E(CAAR) = 0 \leftrightarrow H_1 : E(CAAR) \neq 0\ .$$