Second-Generation Prediction Markets for Information Aggregation: A Comparison of Payoff Mechanisms

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Abstract

Initial applications of prediction markets (PMs) indicate they provide good forecasting instruments in many settings, such as elections, the box office, or product sales. One particular characteristic of these "first-generation" (G1) PMs is that they link the payoff value of a stock's share to the outcome of an event. Recently, "second-generation" (G2) PMs have introduced alternative mechanisms to determine payoff values which allow them to be used as preference markets for determining preferences for product concepts or as idea markets for generating and evaluating new product ideas. Three different G2 payoff mechanisms appear in existing literature, but they have never been compared. This study conceptually and empirically compares the forecasting accuracy of the three G2 payoff mechanisms and investigates their influence on participants' trading behavior.

We find that G2 payoff mechanisms perform almost as well as their G1 counterpart, and trading behavior is very similar in both markets (i.e., trading prices and trading volume), except during the very last trading hours of the market. These results indicate that G2 PMs are valid instruments and support their applicability shown in previous studies for developing new product ideas or evaluating new product concepts.

Keywords: prediction markets, preference markets, idea markets, forecasting, decision making, new product development

Introduction

Prediction markets (PMs) have emerged as powerful instruments for information aggregation since the late 1980s (Forsythe et al., 1992). Studies in various fields demonstrate their strong forecasting accuracy compared with alternative instruments in politics (Berg et al., 2003, Forsythe et al., 1999), sports (Servan-Schreiber et al., 2004, Spann and Skiera, 2009), and business (Chen and Plott, 2002, Ortner, 1998, Spann and Skiera, 2003). However, these first-generation (G1) PMs rely on the outcome of the event to determine the shares of stock's value, that is, the *payoff value*. Because of this limitation, they apply primarily in settings in which the outcome of a stock's underlying event can be known soon after the market closes. This requirement limits their use, especially in internal corporate settings, because many managerial decisions focus on events that may never occur or have a long time horizon. For example, in decisions among alternate product designs, the outcome of the design (i.e., market success or failure) may be known only a long time hence, and managers will never know what might have happened had they implemented different designs. In that sense, G1 PMs cannot determine the payoff value for new product designs, investments, or other managerially relevant questions.

To overcome this shortcoming, recent research proposes second-generation (G2) PMs, referred to as *preference markets* by Chan et al. (2002), who, along with Dahan and Hauser (2002), refer to these markets as "Securities Trading of Concepts." That is, they trade concepts of products to forecast expected market shares. Subsequent research has focused on investigating the costs, scalability, and duration of G2 PMs (Dahan et al., 2007, Soukhoroukova and Spann, 2005). Another type of G2 PM pertains to the *idea market,* which is similar to preference markets in that participants trade concepts to evaluate the success of different product or design alternatives. However, in contrast with preference markets, idea markets allow participants to create and introduce their own ideas. In these markets, idea creation and evaluation combine into a single instrument; LaComb et al. (2007) Soukhoroukova et al. (2009) support their use to aid in new product development.

Interest in G2 PMs is rising, not only in academics but also in practice. Several PM companies have shifted from offering purely G1 PMs to providing both preference and idea markets. NewsFutures, for example, a leading PM software provider, now includes preference and idea markets in its standard solution portfolio. Firms such as XPree (which offers "Open Innovation Markets") and Nosco ("Idea Exchange") increasingly are shifting away from offering only PMs to enable short- and medium-term forecasting and instead are creating and evaluating innovations.

The main difference between G2 and G1 PMs is that in the former, the outcome of the forecasted events typically cannot be known. In turn, the payoff values of the underlying stock shares cannot be linked to the outcome of the event, so the traditional incentive system breaks down. Alternative payoff mechanisms then base the payoff value on the volume-weighted average trading prices (LaComb et al., 2007), the last fixed price (Chan et al., 2002, Soukhoroukova and Spann, 2005), or the last fixed price when a market closes at a random point in time (Dahan et al., 2007). Despite the likely influence of different payoff mechanisms on forecasting accuracy, no empirical or comprehensive conceptual comparisons provide knowledge about the forecasting accuracy of those payoff mechanisms or their effects on participants' trading behavior.

This article conceptually and empirically compares the forecasting accuracy of the three alternative payoff mechanisms and their influence on participants' trading behavior. In essence, we attempt to identify the best of the three payoff mechanisms and determine how well it works. We organize the remainder of this paper as follows: In the next section, we introduce and discuss G1 PMs, which rely on knowledge of the actual outcome, as well as their applications and shortcomings. Thereafter, we review existing approaches for determining payoff values in G2 PMs, followed by a conceptual comparison. We subsequently present the design of our experimental study, followed by the presentation of results. We conclude with limitations and further avenues for research.

First-Generation PMs with Actual Outcome Payoff Mechanisms

Overview

As their general premise, G1 PMs assemble participants in an online marketplace, where they trade shares of virtual stock whose values relate to the outcomes of events. For example, participants might trade shares of stock tied to the outcome of an election (e.g., “the winner is a Democrat”), such that the value of a share represents the probability or the expected value of that event (Wolfers and Zitzewitz, 2004, Wolfers and Zitzewitz, 2008). If a share of the stock “the winner is a Democrat” has a current value of $0.75 (or $75), it implies a 0.75 probability that the Democratic candidate will win the election. Participants who think the share of stock is undervalued (i.e., believe the true probability is higher) buy shares, whereas those who believe in a lower winning probability sell their shares. By expressing events as stocks, expectations about the events become tradable. The shares’ final values, or *payoff values*, relate to the stock’s underlying event. Therefore, if the Democratic candidate actually wins the election, every participant holding that share of stock receives $1 (or $100) per share (regardless of the final trading value of that share), and those participants who hold shares of the alternative stock “the winner is a Republican” receive $0 per share.

The theoretical foundation for PMs relies on the efficient market hypothesis (Hayek, 1945), which states that asymmetrically dispersed information can best be aggregated by a market mechanism. If the information possessed by all market participants is fully reflected in share prices, the market is efficient (Fama, 1970, Fama, 1991). In the case of efficient markets, at any point in time, market prices reflect the most accurate predictions of all market participants regarding the outcome of the event. Despite some recent evidence that PMs are not fully efficient (Foutz and Jank, 2008), the principle is still very powerful.

Different types of outcomes can be traded in PMs. The most common is the "winner-takes-all" (wta) market, in which shares of one or more stocks are traded and only one of the stocks' underlying events eventually is true. In this case, the shares of the winning stock are valued at $100 (or $1), and all shares of the losing stocks are valued at $0. Theoretical (Wolfers and Zitzewitz, 2008) and empirical (e.g. Cowgill et al., 2008) evidence indicates that share prices, and thus their associated forecasts, correspond to the true probabilities that an event will occur.

The second type of outcome corresponds to a linear rule, whose continuously valued payoff value depends on the actual outcome. For example, to forecast the sales of a product in the next quarter, the typical payoff value would be actual sales or a particular proportion thereof. Thus, if actual sales of the product were $50 million, a share of stock would pay out at $50 (or some other proportional reflection of the total). In turn, a current share value of $55 indicates that actual sales in the next quarter should be as high as $55 million (Spann and Skiera, 2003, Wolfers and Zitzewitz, 2004).

Applications

The first application of PMs occurred in the political environment in 1988 to forecast the winner of a presidential election (Forsythe et al., 1992). Since then, the Iowa electronic markets have run many more U.S. political stock markets (Berg et al., 2003), but there also have been applications in various other areas, including sports (e.g. Rosenbloom and Notz, 2006, Servan-Schreiber et al., 2004, Spann and Skiera, 2009), economics (Gürkaynak and Wolfers, 2005), and even medicine (Holden, 2007). In recent years, PMs have appeared more as a means for forecasting managerially relevant questions, usually in corporate settings. Ortner (1998), studying their forecasting output for project completion deadlines at Siemens, finds high forecasting accuracy. At Hewlett-Packard, Chen and Plott (2002) show that market-based forecasts offer much better forecasting than the company's traditional methods. One of the largest PMs, the Hollywood Stock Exchange (HSX), consistently demonstrates its strong performance in forecasting the box office sales of new Hollywood movies. Spann and Skiera (2003) find in particular that the HSX delivers at least similar and frequently better results than renowned movie experts. Elberse and Anand (2005) also use HSX data to study the effect of advertising on revenues and find a significantly positive relation. Using a large data set across different movies, these authors determine that the effect declines for lesser quality movies. Additional examples of company-related success stories include Google, which has employed several different PMs to forecast business-related figures, such as the number of future Gmail users (Cowgill et al., 2008). Inspired by the early success of markets such as the HSX, a growing number of large companies (e.g., Microsoft, Eli Lilly, Hewlett-Packard) employ internal PMs (Kiviat, 2004).

Other research attempts to study the factors that drive prices in PMs. For example, Elberse (2007) examines the reaction of the HSX movie market to announcements of new stars in the cast and finds a significant impact on predicted sales, which implies that stars drive up the sales of movies. Foutz and Jank (2008) instead employ novel shape analysis to study the effect of price histories on forecasting accuracy and find that certain market shapes can capture phenomena such as herding, which implies that PMs are not fully efficient. In an attempt to understand trading behavior in PMs, Spann et al. (2009) show that individual participants can deliver important managerial insights as lead users in the new product development process.

Shortcomings

Despite these many success stories, G1 PMs have a major shortcoming: The outcome of an event must be known to determine the shares' payoff values and to correctly incentivize participants to trade and reveal their true beliefs. However, for many managerially relevant questions, outcomes may never be known (e.g., which of several alternatives to implement). This type of market, a preference market, provides an example of G2 PMs. Managerial decision making often requires a choice of one among many options (e.g., product features, design alternatives). The success of the chosen option, in theory, can be evaluated eventually, but the outcome of all remaining (non-chosen) options can never be known. Idea markets further this concept by letting participants suggest their own ideas as stocks.

Another type of outcome not entirely captured by preference markets is one that can be known only at a point very distant in the future, such as when the outcome relates to the success of a long-term strategic investment or decision. For example, what will the penetration of RFID-enabled refrigerators in of U.S. households be in 2015? The answer will not be known for a long time (i.e. not until 2015), so G1 PM mechanisms are difficult to apply. However, by using G2 payoff mechanisms, questions of this type can potentially be answered and evaluated within the PM context.

Second-Generation PMs with Alternative Payoff Mechanisms

General approaches

The key challenge when dealing with G2 PMs is to replace the payoff mechanism in G1 PMs with an alternative mechanism that determines the final payoff value of the shares of each stock, independent of the outcome. Generally, this exchange could be conducted in two different ways. First, payoff values might be determined market-internally by using only the data generated from the trading activity. In this case, trading actions serve as proxies for the payoff values, because every trade determines a new share price that reflects the participants' valuation of the stock. By choosing and possibly aggregating a subset of the data, one can try to determine the "true value" of the stock, which serves as payoff value. Second, payoff values might be determined externally through a proxy measure that is independent of the market's trading activity. At this place, experts could evaluate each share of stock and determine the payoff value (Graefe and Weinhardt, 2008, Soukhoroukova et al., 2009).

Several differences mark market-internal and market-external payoff mechanisms. The determination of market-internal payoff values requires no additional effort to gather the necessary information, whereas the effort increases considerably when a group of outside experts is required. The related costs and availability of appropriate sources, as well as the aggregation of expert opinions, can impose significant difficulties. Moreover, if experts participate in markets, we must question the independence of the market and the evaluation mechanisms. Finally, expert evaluations could lead participants to predict (potentially biased) expert decisions rather than submitting their own privately held evaluations, especially if the experts and their biases are known. Therefore, we only consider market-internal payoff values for G2 PMs herein.

Existing studies

Four studies consider market-internal payoff mechanisms for preference and idea markets (Chan et al., 2002, Dahan et al., 2007, LaComb et al., 2007, Soukhoroukova and Spann, 2005). They generally indicate the advantages of market-based methods compared with other instruments, such as costs, scalability, and the existence of biases, yet none provides a test of external validity or forecasting accuracy. Rather, evaluations typically are based on proxy measures, such as the results of conjoint studies, surveys, or Delphi methods.

One type of G2 payoff mechanism bases the payoff on the volume-weighted average price (vwap) over a certain period of time (LaComb et al., 2007):

$$payoff_i^{vwap} = \frac{\sum_t p_{i,t} \cdot q_{i,t}}{\sum_t q_{i,t}}, \text{ with time}(t) \geq vwap\_start \qquad (1).$$

In this equation, $p_{i,t}$ denotes the price of a share of the i-th stock at the t-th trade, $q_{i,t}$ denotes the corresponding number of shares per trade, *vwap_start* is the point in time at which the vwap calculation starts, and *time(t)* is the point in time at which the t-th trade is executed. Because the vwap includes trades over a certain period of time to determine payoff values, it attempts to reduce reliance on single trades.

An alternative G2 payoff mechanism relies on the last price at which a stock traded at a fixed and publicly known point in time, T^{fixed} (Chan et al., 2002, Soukhoroukova and Spann, 2005):

$$payoff_i^{last\ price} = p_{i,\max(t)}, \text{ with time}(t) \leq T^{fixed} \qquad (2).$$

The rationale for this payoff measure derives from the efficient market hypothesis, which states that all available information at the end of the market should be reflected in the last price. Moreover, the concept is easily conveyed to and understood by all market participants.

A third G2 alternative, similar to the previous measure, uses the final trading price but closes the market at a random point in time (Dahan et al., 2007). Therefore, T^{random} is between two prespecified points in time, *random_start* and *random_end*, and the last price random close can be computed as:

$$\begin{aligned} & payoff_i^{last\ price\ random\ close} = p_{i,\max(t)}, \text{ with} \\ & \text{time}(t) \leq T^{random} \wedge random\_start \leq T^{random} \leq random\_end \end{aligned} \qquad (3).$$

This mechanism thus attempts to avoid last-minute price manipulations.

Although these three G2 payoff mechanisms appear in previous studies, their forecasting accuracy has not been compared. Moreover, all payoff mechanisms aim at eliciting participants' true beliefs about the event, but no investigations address whether they influence trading behavior systematically. We focus on these two issues.

Conceptual Comparison of Payoff Mechanisms

Expected accuracy of G1 and G2 payoff mechanisms

Wolfers and Zitzewitz (2004) cite three reasons G1 PMs with actual outcome payoff mechanisms should perform well: They provide (1) incentives to seek information, (2) incentives for truthful information revelation, and (3) an algorithm for aggregating diverse opinions. The essential idea of PMs is that updates of existing information earn rewards when the new information is more accurate than existing information but penalties when the new information is less accurate. Ultimately, the payoff value relates to the occurrence of a particular event, so its occurrence (or non-occurrence) determines how much participants earn. In turn, both public and private information should be incorporated into prices.

In contrast, the alternative payoff mechanisms — volume-weighted average price (vwap), last price, and last price random close — do not depend on the actual outcome, and the payoff values might be completely independent of the "true" outcome. In theory, this shift should alter the trading strategies in the markets. That is, in G1 PMs in which the payoff values are based on the actual outcome, participants' investment decisions should rely on the expected actual outcomes, whereas in G2 PMs, participants must predict the vwap or last traded price. Therefore, they have no incentive to reveal their private information, because doing so does not necessarily earn them rewards from the mechanism. A form of information cascade might result (Bikhchandani et al., 1992), such that private information gets underweighted and transactions instead depend on transactions by other participants. Although this informational inefficiency might occur in PMs with actual outcome payoff values (Anderson and Holt, 1997), the effect is likely larger in G2 PMs, because portfolio performance essentially depends not only on the owner's own assessments but also to a large extent on the assessments of others, that is, the majority of remaining participants. In summary, we expect G1 PMs with payoff values based on actual outcomes to be superior in terms of prediction accuracy than G2 PMs with payoff values based on alternative payoffs.

Expected trading behavior in G2 PMs

Alternative payoff mechanisms in G2 PMs may affect the overall prediction accuracy of the market, as well as individual participants' trading actions. However, to understand individual trading behavior, we first investigate the market mechanism, or the rule for making individual trades.

Market mechanisms in PMs

Most PMs employ automated market makers (AMMs) as trading mechanisms, because they tend to be very illiquid (Hanson et al., 2006, Pennock, 2004). These AMMs can execute buy and sell orders at any point in time, so trading is always possible, unlike in standard continuous double auctions, which require matching between buy and sell orders. We use Hanson's (2003, 2007) market scoring rules, the most widely used AMM, which adopt a continuous price function that sets the share price, depending on the number of shares in the market. By buying or selling shares of stocks, the participant can drive the price of the shares up or down, from an old to a new price. The mean share price that a participant pays for a certain amount of shares then is roughly in the middle between the old price and the new price. For example, assume the current share price is \$50 (old price). By buying 10 (20) additional shares, a participant drives the price up to \$60 (\$70) (new price)[1]. However, the price paid for 10 (20) shares falls between \$50 and \$60 (\$70) (roughly \$50.5 for the first, \$51.5 for the second, \$59.5 for the tenth, \$69.5 for the twentieth share, etc.), because the continuous price function prices every single share of stock differently. Therefore, the participant pays roughly \$55 (\$60) for each of the 10 (20) shares to drive the price from \$50 to the new final price of \$60 (\$70). The trade is now described as "Buy 10 (20) at a price of \$60 (\$70)." We consider the new price for the description of the trade, as it is the trader's final valuation of the share, rather than the mean price paid. Moreover, the mean price paid also incorporates the old price, which in turn should not matter for the description of the current trade.

Trading behavior

To analyze trading behavior, we consider two aspects: myopic strategies, which focus on participants' considerations for each trade, and the resultant possible herding behavior. In vwap markets, which determine a stock's payoff value according to the volume-weighted average price over a period of time, the trading period consists of two phases: a first phase when trades are not considered for the calculation of the vwap, prior to *vwap_start*, and a second phase, in which every trade gets taken into account for the vwap calculation. In theory, from a myopic point of view, trading behavior should differ significantly between these two trading phases: Every trade executed in the second phase should result in a loss for the participant if he or she executes only small trades. For illustration, consider a simple scenario: Assume a vwap trading history of 5 shares traded at a price of $50. The current price is $50 (old price). The participant then decides to buy two shares at prices $50.5 and $51.5, which drives the price, through the AMM, to $52 (new/last fixed price). On average, the participant has paid $51 for each share of stock. The current payoff (calculated by vwap) is lower than the invested capital; specifically, the vwap for this transaction (see Equation 1) equals (5 × $50 + 2 × $52)/(5 + 2) = $50.57, which is lower than the $51 that was paid for each share. Therefore, there is little incentive for a participant to conduct such a transaction.

The scenario differs for trades of more shares. When buying 10 shares, for example, the price would move up to $60, and the cost for this transaction would be the mean between $50 and $60, or $55 per share. In this case, the vwap rewards the transaction because the ensuing payoff would reach as high as (5 × $50 + 10 × $60)/(5 + 10) = $56.67, higher than the average invested capital of $55 per share. From a myopic view, the participant has more incentives to initiate larger price changes, which implies trading more shares, to increase the price changes and thus the price volatility. Therefore, we expect trading activity to be greater in the second trading phase, when the vwap calculation kicks in, than in the first phase. Moreover, we expect this trend to increase near the end of the markets, as the vwap gains more and more trading memory and requires larger trading quantities to alter that memory. As another potential consequence, herding might result when participants receive rewards from moving prices in the same direction.

[1] The speed at which prices move is controlled via one parameter

The vwap mechanism can influence an individual participant's trading behavior, though similar effects also might occur with other G2 payoff mechanisms. In last price markets, from a myopic point of view, every trade is immediately profitable if it is the last one. When buying, for example, 10 shares of stock, the price for each share is $55 on average. Yet the last fixed price of the last trade is $60, which also represents the payoff value. These considerations are analogous to (short) sales.

When a participant has bought (sold) shares previously, it makes even more sense for him or her to buy more (sell) shares later. With every purchase (sale), a participant not only profits from the recently bought (sold) shares but also increases (decreases) the value of shares in the portfolio. Therefore, participants obtain strong rewards for their herding behavior (i.e., price moves in the same direction) near the end of the market. Trading activity thus should increase at the end of last price markets, especially the very last moments.

In contrast, we do not anticipate last minute trading in last price random close markets, because the closing time of the markets is unknown to participants. Therefore, herding behavior and last-minute movements should be weaker.

Experimental Design

We use a field experiment to test the different payoff mechanisms and compare the forecasting accuracy of G2 payoff mechanisms (G1 mechanism as a benchmark) and the impact of G2 trading mechanisms on individual trading behavior. Because we cannot assess true performance in markets with events whose outcomes will never occur, we base our experiment on forecasting events that do occur and to analyze the forecasting accuracy of the different payoff mechanisms. Prior research indicates that the type of event to be predicted may have an effect on the market outcome (Rosenbloom and Notz, 2006). Therefore, unlike most studies, which focus on one topic, we base our analyses on three different topics, namely, politics, sports, and general economic issues.

We ran experiments pertaining to these three topics in the spring term of 2008 at a major U.S. east coast university. The subjects were 78 MBA students. With three alternative payoff mechanisms to be tested and the actual outcome mechanism as a benchmark, we obtained four different types of markets. We randomly assigned each student to one of the four payoff mechanisms. Students did not participate in the same payoff mechanism more than once, to eliminate possible learning effects. Moreover, to achieve more robust results, we ran each market experiment in two replications, with each student assigned to either the first or second replication. These assignments resulted in a total of eight different markets for each topic, or 24 total different markets. Each topic consisted of nine to eleven stocks, for a total of 4 × 2 × (11 + 10 + 9) = 240 single stocks (see

Table 1). We used 17 winner-takes-all stocks and 13 linear stocks (see the Appendix).

The initial endowment of each participant consisted of $10,000 in virtual currency. After each round of the experiment, we reset participants' portfolio values to the initial values to avoid endowment effects across experiments. We added their profits (or losses) to determine their overall ranking. The top 10% of all students received 110% of course credit (equivalent to an A+); the top 90% to 60% received 100% of course credit (i.e., an A); those ranked in the 60–20 percentiles received 90% (i.e. a B); and the lowest 20% received 80% (i.e., a C). Luckner and Weinhardt (2007) show that such a rank-order tournament incentive scheme leads to the best results in terms of prediction accuracy in play money markets. We also offered four gift certificates with values up to $50; however, we believe that the course credits were a much greater incentive than the promise of gift certificates. All students had this information before the start of the experiments, which means it was transparent to all participants that they had to maximize their portfolio values to obtain a high standing in the field. Participants also were instructed repeatedly to remain aware of the individual payoff mechanisms orally, by e-mail, and within the trading system at different places, on the main screen, and in the descriptions of the stocks.

Factor	Number of Levels	Specification
Topics	3 (1)	• Primaries on March 3, 2008 (also experts) • “Final Four” NCAA basketball games on April 5, 2008 • Economic events in or at the end of April
Payoff mechanism	4 (1)	• Based on actual outcome (also experts) • Based on vwap of last 48 hours • Based on last fixed price • Based on last fixed price with random close of market (within 4 hours of close of all markets)
Replications	2 (1)	• Each market with 9–10 student participants (24 expert participants)
Total number of markets	3 · 4 · 2 = **24** (1 · 1 · 1 = **1**)	
Stocks	10 on average per market (11)	• Overall 17 winner-takes-all and 13 linear stocks (4 winner-takes-all, 7 linear)
Total number of stocks	24 · 10 = **240** (1 · 11 = **11**)	

Table 1: Experimental design (expert markets in parentheses)

The calculation of the vwap took place during the second half of the trading period, specifically, the last 48 hours, which is an appropriate period for two reasons: It is short enough to let the market prices move away from the initial starting prices but long enough that prices are not moved easily by single trades. In the last price random close markets, they closed at a random point in time during the last 4 hours of trading. Both time spans were transparent on the Web site for all affected participants.

To establish the actual outcome markets’ validity as a benchmark, we created another, self-contained market for the first topic (election primaries) with 11 stocks, which consisted of 24 experts from political consultancy firms across the United States. Although the only extrinsic incentive for the participants was a $100 gift certificate for the winner, we believe that their displays in the rankings were sufficient incentive for them to perform well, due to peer pressure. The payoff values reflect the actual outcomes of the events. As software, we used a self-developed trading platform that we tested in several previous experiments and field studies.

We also allowed for the short-selling of shares, which, in conjunction with the market mechanism (i.e. the AMM), enabled participants to move stock prices in their desired direction at any point in time. The markets were completely identical, except for the payoff mechanisms and their descriptions. For example, the descriptions of the stock "A margin greater than 10 percent by either Clinton or Obama in Ohio" were as follows for the markets with these respective payoff values:

- *Actual outcome:* "The price of this share of stock denotes the probability that the margin of votes by either Obama or Clinton is greater than 10 percentage points in the Ohio primaries […] After the elections, the stock will cash out after the primaries at $100 if the margin is more than 10 points, else at 0$. […] The market closes Monday, March 3rd, 8 PM."
- *Volume-weighted average price:* "The price of this share of stock denotes the probability that the margin by either Obama or Clinton is greater than 10 percentage points in the Ohio primaries. […] The stock will cash-out at the **volume-weighted average price**, determined between Saturday, March 1st, 8PM, and Monday, March 3rd, 8PM."
- *Last price:* "The price of this share of stock denotes the probability that the margin by either Obama or Clinton is greater than 10 percentage points in the Ohio primaries. […] The stock will cash-out at the **last fixed price** before the close of the markets on Monday, March 3rd, 8 PM."

- *Last price random close:* “The price of this share of stock denotes the probability that the margin by either Obama or Clinton is greater than 10 percentage points in the Ohio primaries. […] The stock will cash-out at the **last fixed price** before the close of the markets. The markets will close at a **random point in time** on Monday, March 3rd, between 4 PM and 8 PM.”

Results

We next discuss the results of our experiments. Because we have both winner-takes-all stocks, whose share prices range from 0 to 100, and linear stocks, whose share prices can range between two arbitrary numbers, we linearly normalize the final price of stocks with continuous payoffs in the range 0–100. For example, we normalize the final price of a stock with a continuous payoff of \$55, which traded between \$40 and \$60, to a price of \$75 (= (\$55 – \$40)/(\$60 – \$40)). This normalization enables us to examine both types of stocks simultaneously.

Forecast accuracy

We investigate the forecast accuracy of the different payoff mechanisms according to their mean absolute forecast errors (MAE), which equals the absolute difference between the forecast and the true outcome (see Table 2).

Payoff Mechanism	Actual outcome with Students	Actual outcome with experts	Vwap	Last price	Last price random close
Topic 1 (Politics)					
MAE	18.15	19.72	30.70	23.39	31.66
Std. error	3.62	7.27	5.03	4.21	5.10
N	22	11	22	22	22
Topic 2 (Sports)					
MAE	31.22		27.77	30.49	29.30
Std. error	6.50		6.31	6.66	5.71
N	20		20	20	20
Topic 3 (Economy)					
MAE	39.28		46.05	48.37	41.83
Std. error	6.34		6.93	5.85	5.70
N	18		18	18	18
All					
MAE	28.85		34.33	33.25	33.92
Std. error	3.37		3.63	3.49	3.24
N	60		60	60	60

Table 2: Mean absolute errors across topics

To evaluate the forecasting accuracy of the student markets and confirm them as a valid benchmark, we compare their forecasting accuracy to that of the expert markets, which considered 11 stocks in the first topic. The actual outcome student markets performed no worse than the expert markets; in fact, they performed slightly better, with a MAE of 18.15 compared with a MAE of 19.72 for the expert markets. However, the difference is not significant (paired t-test, paired for each stock with the expert markets and the average of the two actual outcome market stocks), which suggests that the forecasting accuracy by the students is not significantly different than that by the experts.

When comparing all payoff mechanisms, we find that the actual outcome markets (i.e., with G1 mechanisms) perform best, which is not surprising and fits our hypothesis. The best G2 performance comes from the last price markets, with an error of 33.25 (absolute difference 4.40); the vwap and last price random close markets perform only marginally worse, with MAE of 34.33 and 33.92, respectively.

In line with results obtained by Rosenbloom and Notz (2006), we find that the forecasting accuracy varies between different topics. That is, error for the second topic (sports) is lower for the G2 markets than for the actual outcome (G1) markets.[2] In contrast, for the two other topics, the actual outcome markets outperformed the alternative markets, with an absolute difference of at least of 5.24 percentage points (significant at least at the 10% level, paired t-test) in the first topic and 2.55 (not significant, paired t-test) in the third.

Stock Type	***Linear Stocks***				***Winner-Takes-All Stocks***			
Payoff mechanism	**Actual outcome**	**Vwap**	**Last price**	**Last price random close**	**Actual outcome**	**vwap**	**Last price**	**Last price random close**
MAE	14.01	19.78	18.77	17.71	48.25	53.36	52.19	55.12
Std. error	2.69	3.54	3.24	2.50	4.74	4.90	4.74	3.84
N	34	34	34	34	26	26	26	26

Table 3: Mean absolute errors across stock types

Because we consider two different types of stock (linear versus winner-takes-all), we also analyze them separately as their type may have different effects on forecasting accuracy. The error of a winner-takes-all stock can be fairly high, even when the forecast is correct. For example, if the true probability of an event is 51:49 and the market correctly predicts a 51% probability, the error can be as great as 49 percentage points. In our experiment, the actual outcome mechanism markets perform better for both stock types, with errors of 14.01 for linear stocks and 48.25 for winner-takes-all stocks. However, the results for the G2 payoff mechanisms are less consistent. The last price random close markets perform best for linear stocks, with an error of 17.71,[3] and they perform worst for winner-takes-all stocks, with an

[2] Specifically, 27.77, 30.49, and 29.30, compared with 31.22, which is not significant according to the paired t-test.

[3] Not significant compared with the actual outcome markets, 10%, paired t-test.

error of 55.12.[4] In the vwap and last price markets, the latter outperform the former for both stock types with MAEs of 18.77[5] versus 19.78,[6] respectively, for winner-takes-all and 52.19 versus 53.36,[7] respectively, for linear.

To investigate the impact of different payoff mechanisms on forecasting accuracy while controlling for stock type and topic, we next set up the following linear model. The dependent variable is the (natural) logarithm of the absolute error, plus 1[8]:

$$
\begin{aligned}
e_{i,p,r} = \beta_0 & \\
& +\beta_1 \cdot \mathrm{DV\_linear_i} + \\
& +\beta_2 \cdot \mathrm{DV\_topic\_2_i} \\
& +\beta_3 \cdot \mathrm{DV\_topic\_3_i} \\
& +\beta_4 \cdot \mathrm{DV\_vwap_i} \\
& +\beta_5 \cdot \mathrm{DV\_last\_price_i} \\
& +\beta_6 \cdot \mathrm{DV\_last\_price\_random\_close_i} \\
& +\mu_{i,p,r}
\end{aligned} \qquad (4),
$$

where

$e_{i,p,r}$:	dependent variable, $e_{i,p,r} = \ln(abs\_error_{i,p,r} + 1)$, of the *i*-th stock, payoff mechanism *p*, and the *r*-th replication.
$\mathrm{DV\_linear_i}$:	dummy variable, equal to 1 if the *i*-th stock type is linear and 0 if stock type is winner-takes-all.
$\mathrm{DV\_topic\_X_i}$:	dummy variable, equal to 1 if the *i*-th stock is part of topic *X* and 0 otherwise.
$\mathrm{DV\_P_i}$:	dummy variable, equal to 1 if the *i*-th stock's payoff mechanism is P and 0 otherwise.
$\mu_{i,p,r}$	residual of the *i*-th stock with payoff mechanism *p* and the *r*-th replication.

We control for topics (two dummy variables), because they likely influence the forecasting accuracy of the markets. We have a total of N = 240 observations to estimate our model.

---

4 Not significant compared with the actual outcome markets, 10% level.
5 Significant at 5%.
6 Significant at 10%.
7 Neither is significant at 10%.
8 Absolute errors are not normally distributed, requiring the logarithmic transformation and, because of the existence of zero values, the addition of 1 to all absolute errors.

	Model		
	ß	*sig.*	
Constant	3.413	(0.000)	***
DV_linear	-1.242	(0.000)	***
DV_topic_2 (sports)	0.075	(0.562)	
DV_topic_3 (economy)	0.491	(0.000)	***
DV_vwap	0.256	(0.096)	*
DV_last-price	0.227	(0.138)	
DV_ last-price-random-close	0.303	(0.049)	**
R^2 / adj.	0.413	/ 0.398	
F-value	27.333	***	
N	240		

Table 4: Regression results for influence on absolute forecasting error

* Significant at 0.1 level.
** Significant at 0.05 level.
*** Significant at 0.01 level.

The results in Table 4 show that linear stocks have a significantly lower absolute forecasting error than do winner-takes-all stocks, as we have suggested. Also, the outcomes for the economy (topic 3) are less accurate than those for the remaining topics. Regarding the different payoff mechanisms, the last price mechanisms perform as well as actual outcome markets, which is quite remarkable. For the other two alternative mechanisms, vwap and last price random close, the prediction accuracy decreases (though the difference in the results is not significant at the 10% level).

Trading behavior

As we noted, we expect different payoff mechanisms to have different effects on participants' trading behavior. We investigate whether the data support this expectation. To examine whether alternative payoff mechanisms cause a systematic deviation in trading behavior, we compare this behavior with that of participants in actual outcome markets. Assuming that G1 markets produce "normal" trading behavior, we investigate the G2 deviations, controlling for stock- and topic-specific effects, both of which affect forecast accuracy. By computing pair wise differences of the prices and cumulative traded quantities between actual and alternative mechanisms, we can filter out effects such as forecasting difficulty or general lack of knowledge about certain events.

Price difference between G1 and G2 markets

We compute the mean difference of prices between alternate (G2) and actual (G1) markets for each stock and each replication, as follows:

$$\Delta price_{p,z} = \frac{1}{30 \cdot 2} \sum_{i=1}^{30} \sum_{r=1}^{2} \left(p_{i,p,r,z} - \frac{p_{i,actual,1,z} + p_{i,actual,2,z}}{2} \right) \quad (5),$$

where $p_{i,p,r,z}$ is the price of the *i*-th stock with a payoff mechanism *p* at the *r*-th replication at time *z*. We compute the mean differences (black solid lines) and corresponding 95% confidence bounds (dashed lines) for each payoff mechanism, as we show in Figure 1. Figure 1, in the first half of the trading period, when the vwap calculation has not yet started, the mean difference falls below the horizontal zero-level line. This difference signifies that the prices of the alternative payoff markets are less than those of the actual outcome markets, though not significantly. (Note that the confidence bounds include zero.) As soon as the vwap calculation starts, the vwap share prices start to increase and then stay above the actual market prices, though again not significantly until the last eight trading hours. This result is in line with our conceptual considerations; we expected a strong movement of prices in the second half of the trading phase. Although in theory, prices could move in either direction, we clearly determine that prices rise significantly. In the last trading hours in particular, we find that vwap markets exhibit a type of herding behavior, which is not limited to the last minutes of trading but rather starts hours before the close. This observation of overpricing mirrors a previous vwap study (LaComb et al., 2007, Table 2), in which most share prices were higher than the starting prices, even with a continuous double auction, rather than an AMM, as a market mechanism.

In last price markets (middle panel), we find that prices are never significantly different from actual payoff market prices. Rather, they are slightly underpriced most of time, with the exception of the last few trading hours, when prices increase and average almost the same as the actual payoff markets prices. We expected this behavior to be much more extreme, such that prices would move even more steeply toward the end. We therefore analyze last minute trading further subsequently.

Finally, in the last price random close markets, the effect is similar. Over time, prices do not differ significantly from actual outcome market prices. However, as in the last price markets, prices increase in the final trading hours. We did not anticipate this increase in theory, but herding behavior seems to have commenced a few hours before the close of the markets.

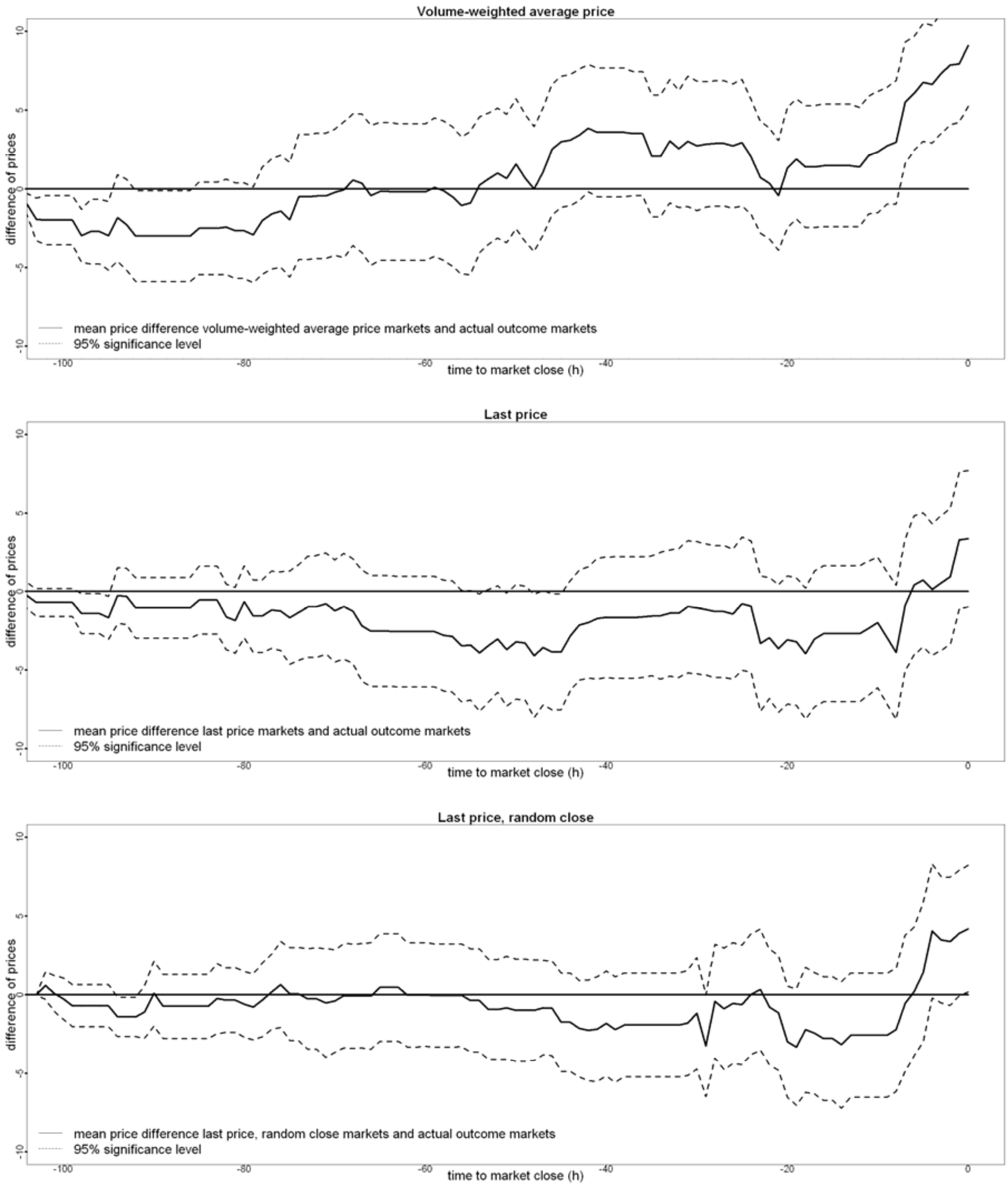


Figure 1: Differences across time of prices between markets with alternative payoff mechanisms and markets with actual outcomes.

Notes: Dashed lines signify 95% confidence intervals.

Trading volume difference between G1 and G2 markets

Similar to our analysis of the mean differences of prices, we study the mean differences of cumulative trading quantities to determine the trading behavior of market participants. We denote $Q_{i,p,r,t}$ as the cumulative number of traded shares of the *i*-th stock, with payoff mechanism *p* and in the *r*-th replication until a point in time *z* as follows:

$$\Delta traded\_shares_{p,z} = \frac{1}{30 \cdot 2} \sum_{i=1}^{30} \sum_{r=1}^{2} \left(Q_{i,p,r,z} - \frac{Q_{i,actual,1,z} + Q_{i,actual,2,z}}{2} \right) \quad (6).$$

We depict the results in Figure 2. In vwap markets, a significantly higher number of shares gets traded (cf. actual markets), and the effect intensifies toward the end of the trading period. These results support our expectations; we stipulated that trading intensity should be higher after the start of the vwap calculations because larger trades would be more profitable for participants.

A weaker effect emerges for the last price and last price random close markets. Trading activity is constantly higher than in actual outcome markets; however, this effect is not significant (the confidence bounds include zero). This result is what we expected, because from a myopic point of view, every trade should be profitable (without inventory considerations). However, participants seem to input their beliefs early into prices, despite alleged downsides when it comes to their evaluations.

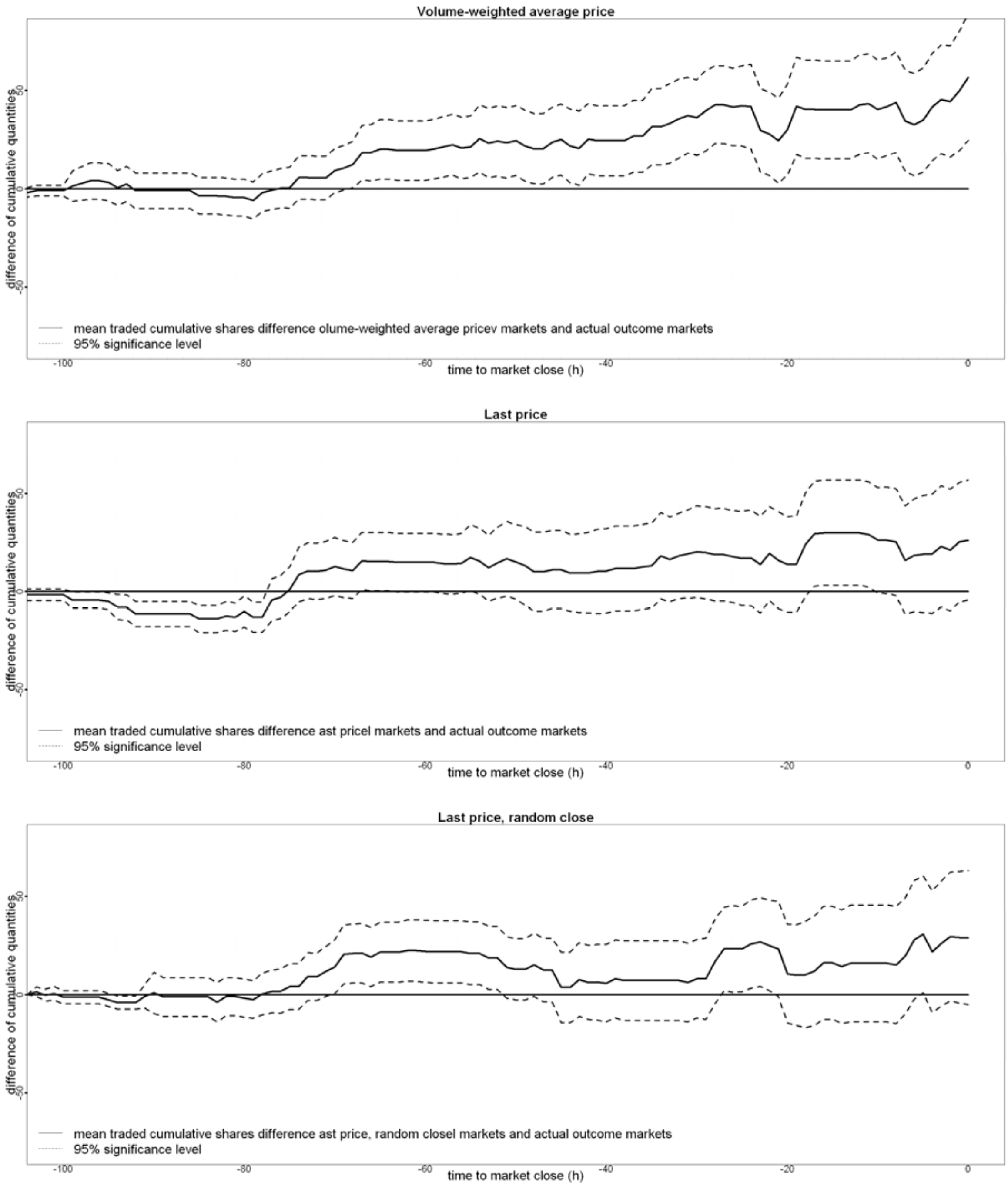
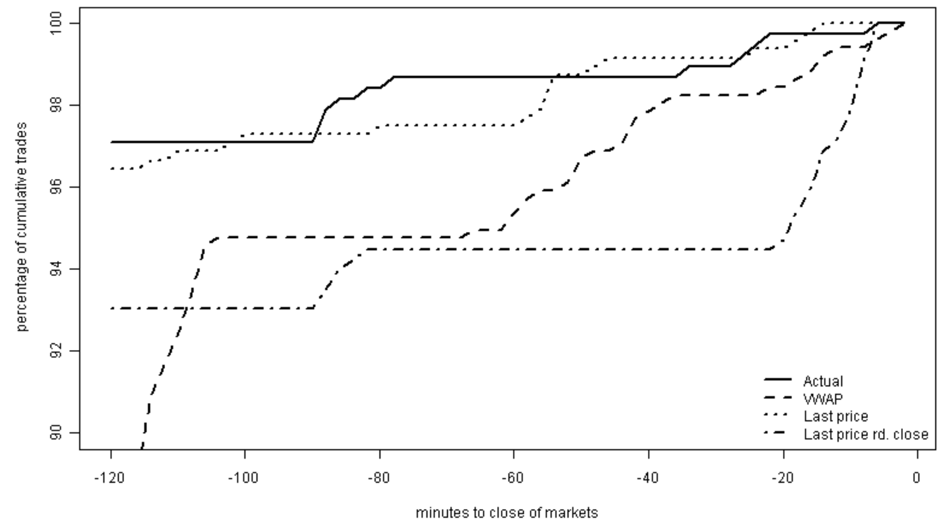


Figure 2: Differences across time of cumulative trading quantities between markets with alternative payoff mechanisms and markets with actual outcomes.

Notes: Dashed lines signify 95% confidence intervals.

Last minute trading

We hypothesized that last minute trades, just before the close of the markets, should particularly happen in last price markets. To uncover this behavior, we focus on the last two hours before the close of the markets and determine the cumulative percentage of all trades and cumulative percentage of all traded shares.



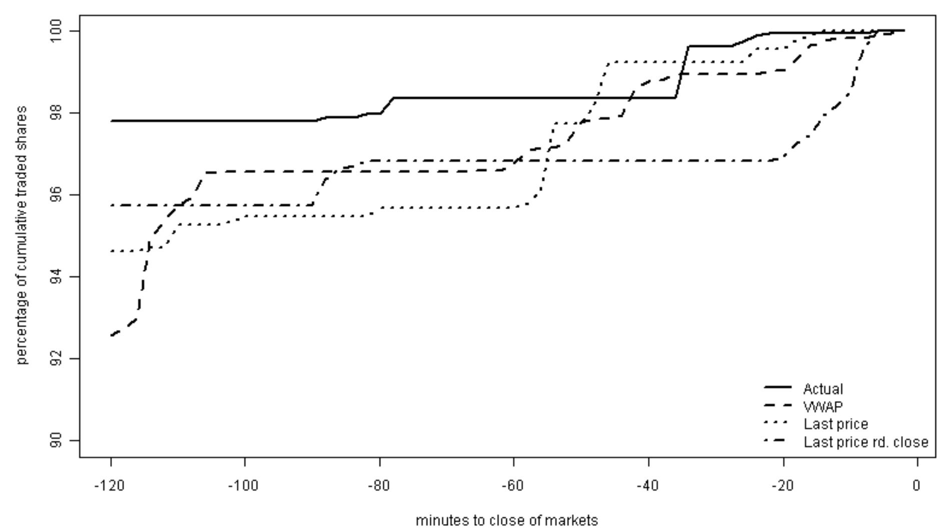


Figure 3: Cumulative number of trades (upper figure) and traded shares (lower figure) in the last minutes of markets with alternative payoff mechanisms and markets with actual outcomes

As Figure 3 reveals, few trades occur and few shares are traded in the actual outcome markets, because 98% of all trades take place more than two hours before the close. Thus, we cannot detect any particular last minute trading activity for this payoff mechanism. In contrast, the vwap payoffs exhibit considerable trading during the two last hours. Two hours before the close, only 87% of all trades had been executed, and 93% of shares were traded. These numbers rather consistently climb to 100%, though we observe no very last minute trading.

Although we did not expect this behavior in the last price markets, we do not find any very last minute trading (dotted line). Two hours before the close, more than 96% of trades had been executed, and more than 94% of shares were traded. Surprisingly, during the very last minutes of trading, we again cannot detect any high trading actions.

Also unexpectedly, we detect the highest very last minute trading behavior in the last price random close markets. That is, 20 minutes before the close of the markets, only 94% of all trades had been executed, and 96% of all shares traded, which is relatively low compared with the other markets. In this case, because the markets close randomly, it appears that constant trading took place in the last trading hours, and the participants appeared to hope for the markets to close after they traded their respective stocks.

Conclusion

Although so-called "first-generation" (G1) PMs have superior forecasting accuracy, their usage remains limited to forecasting events whose outcomes can be determined in the short or medium term. We instead investigate whether a new type of PMs, which we label "second-generation" (G2) PMs, can determine forecasts of events that either never occur or only occur in the long term. By experimenting with three different topics that require forecasts of actual events, we (1) obtain a benchmark, namely, G1 PMs with payoff values based on the actual outcome, and (2) for the first time, compare the forecast accuracy of alternative G2 payoff mechanisms.

Markets in which the shares' payoff values are based on the last fixed price only perform 4.4 percentage points worse on average than PMs whose payoff values are based on the actual outcome. Markets with alternative payoff mechanisms should perform worse than actual payoff mechanisms, yet this absolute difference of error is surprisingly low. This finding is particularly notable because G1 PMs consistently have shown superior accuracy compared with the alternative instruments. Also surprisingly, the other alternative payoff mechanisms, vwap and last price random close, perform only slightly worse than the last price mechanism.

Our results are remarkable, considering the conceptual disadvantages of the G2 payoff mechanisms. In the vwap payoff, we might expect participants to trade extensively during the time the vwap is being determined, to influence prices in their desired direction. However, prices did not differ significantly from those of the benchmark until the last few hours. We also expected herding behavior in last price markets, especially right before the close of the markets, but surprisingly, we could not detect any.

In summary, this study supports the use of G2 PMs, as employed by Chan et al. (2002), Soukhoroukova and Spann (2005), Dahan et al. (2007), and LaComb et al. (2007). Moreover, we reveal that using experts to determine payoff values (Graefe and Weinhardt, 2008, Soukhoroukova et al., 2009), which can be costly, difficult, and biased, may not be required for G2 PM applications. This study therefore encourages further thinking about new application areas for G2 prediction markets. The problems related to the use of alternative payoff mechanisms are much less severe than what might be expected, and the particular choice of any available payoff mechanisms does not notably influence the results. Thus, G2 PMs seem to offer a promising tool to support new product development through preference or idea markets, because they can tap the collective intelligence of a crowd.

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Appendix

Question/Stock	**Stock Type**	**Min. Value**	**Max. Value**	**Actual Outcome**
Topic 1 (Politics)				
A margin greater than 10 percent by either Clinton or Obama in OH	wta	0	100	100
Obama sweeps 03/04/2008 primaries	wta	0	100	0
Edwards endorses before or on the day of the election	wta	0	100	0
Clinton suspends or drops out of the race on 3/4/08	wta	0	100	0
% of popular votes Clinton gets in OH	linear	0	100	54
% of women votes Clinton gets in OH	linear	0	100	57
% of men votes Clinton gets in OH	linear	0	100	50
% of African American votes Obama gets in OH	linear	0	100	89
% of White votes Obama gets in OH	linear	0	100	34
% of popular votes McCain gets in OH	linear	0	100	60
Number of states × 10 Clinton wins on 3/4/08	linear	0	40	30
Topic 2 (Sports)				
Memphis wins against UCLA	wta	0	100	100
UNC wins against Kansas	wta	0	100	0
3-pt field goal shooting percentage of Memphis in Memphis-UCLA game	linear	0	100	33.33
Overall shooting percentage of UCLA in Memphis-UCLA game	linear	0	100	37.5
Percent of Memphis rebounds out of total rebounds in Memphis-UCLA game	linear	0	100	54.55
Memphis-UCLA game's top scorer is from UCLA	wta	0	100	0
Free throw percentage of UNC in game UNC-Kansas	linear	0	100	86.7
Percent of Kansas turnovers out of total turnovers in game UNC-Kansas	linear	0	100	51.35
Percent of UNC fouls out of total fouls in game UNC-Kansas	linear	0	100	40

UNC-Kansas game's top scorer is from Kansas	wta	0	100	100
Topic 3 (Economy)				
Unemployment rate in April times 10	linear	40	60	50
Consumer Price Index (CPI) surpasses 4.8% in April	wta	0	100	0
Dow Jones at end of April divided by 100	linear	100	140	120.82
Euro-Dollar exchange rate is above $1.60 at end of April	wta	0	100	0
Microsoft has taken over Yahoo! by the end of April	wta	0	100	0
Crude Oil Spot Market Price at end of April	linear	100	140	113.7
Eastman Kodak's Q1 earnings are positive	wta	0	100	0
Sun Inc.'s earnings per share in Q3 of the fiscal year 2008 in cents	linear	10	30	10
Justice department approves Delta/Northwest merger by the end of April	wta	0	100	0

Table A1: Questions/stocks in experiment

Notes: wta = winner takes all.