Information Aggregation Efficiency
in Virtual Prediction Markets
The Role of Trader Type, Allocative Efficiency and Source of Information

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The author declares that the text and work presented in this Master thesis is original and no sources other than those mentioned in the text and its references have been used in creating the Master thesis.

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1 Introduction

1.1 Summary

Prediction markets have shown excellent information aggregation and forecasting abilities. Markets can efficiently consolidate information that is widely dispersed among a number of individuals. In such markets, securities of future outcomes are traded on virtual trading platforms. Resulting market prices reflect a market consensus about the likelihood of future outcomes.

The development of electronic markets has enabled a broader application of markets and improved market design options for the purpose of business forecasting and decision support. Prediction markets are expected to become a central information management instrument of organizations in the future. However, little is known about the mechanism of information aggregation in such markets. A predominant theory of information aggregation based on differences in trader types has been proposed in literature. It states that a certain trader type shows superior ability to identify relevant information and show less cognitive biases. It states further that this trader type is responsible for efficient information aggregation. Empirical observations made in several experimental markets militate against such a theory.

This thesis seeks to challenge the trader-based theory by testing its assumptions with regard to prediction accuracy and by proposing and testing an alternative theory based on allocative efficiency. The alternative theory accounts information averaging through a double auction mechanism as determinant of efficient information aggregation in markets. It states further that information aggregation may be improved by a higher degree of allocative efficiency. Both theories are empirically tested through a laboratory experiment which includes a set of combined.

The results indicate that the trader type seems to be less relevant for efficient information aggregation while no direct relationship between allocative efficiency and information aggregation efficiency can be found. Instead, the results indicate sources of information to affect efficient information aggregation.

A better understanding of the information aggregation mechanism is crucial for both researchers and market designers. The results of this research will help market designers with recommendations for achieving higher forecast accuracy, a better interpretation of market results and improved market design.

1.2 Introduction to the Topic

1.2.1 Interest of Research Topic

Prediction markets have recently been selected as one of the most emerging technologies in Gartner's Hype Cycle (Gartner 2005). Ongoing corporate research projects with notable firms such as HP, Eli Lilly, Microsoft, Goldman Sachs, Deutsche Bank, Siemens and BP show that this issue gets considerable attention by the business community (Economist 2004, TIME 2004). Such markets provide a cost-effective solution to aggregate private information held by and dispersed among individuals. However, Gartner does not expect this technology to reach maturity before 2015 (Gartner 2005). Research needs first to describe the mechanism and the conditions that account for effective information aggregation in such markets in order to ensure a more reliable implementation and performance.

1.2.2 Prediction Markets

Prediction markets aggregate private information from individuals in order to predict the likelihood of future events. The markets include a double auction trading mechanism that allows buyers and sellers to submit bids simultaneously in a continuous manner and foster transactions at competitive price levels. In such markets, marketers trade securities whose value or payoff is tied to the outcome of uncertain future events. Resulting market prices reflect aggregated information or a “market consensus” about the likelihood of the future outcome. By that way, market participants have an incentive to contribute their private information to the market through their trading behaviour.
Prediction markets have shown higher prediction accuracy than other forecasting methods in practice, suggesting their efficient information aggregation abilities[1].

Acoording to van Bruggen et al. (2006) Prediction markets are especially valuable in institutional forecasting problems. Such forecasting problems arise if little relevant data is available, if there is high volatility and uncertainty of individual forecasts, if no single individual can make a perfectly accurate forecast in advance, if there are informants who disagree and differ in expertise and if forecast needed to be updated continuously.

1.2.3 Information Aggregation Efficiency

Information aggregation efficiency is defined as the ability of markets to consolidate all fragments of information relevant to accurately predict a future outcome into an aggregated metric from its participants. This notation follows the definition by Rhode and Strumpf (2003)

[1] For an overview see chapter 2.1

who claim that efficient futures markets must provide the best prediction of future events given the current information available from market participants. Information aggregation efficiency can be measured in terms of relative prediction accuracy. This notion refers to the comparison of absolute forecast errors between different forecast metrics obtained from the same market or from another market with different settings but similar to-be-predicted event. For instance, the comparison of mean individual forecasts with last transaction prices of the same market or the comparison of last transaction prices of two different prediction markets that aimed to predict the same event.

1.2.4 Marginal Trader Hypothesis

While many researchers have investigated the level of prediction accuracy achieved by several prediction markets few have attempted to explain the information aggregation mechanism itself. A predominant theory of information aggregation has been proposed by Forsythe et al. (1992). The theory has its theoretical roots in classic capital market theory. It claims that information aggregation in prediction markets is determined by a small subgroup of market participants, called “marginal traders” who usually submit orders at marginal prices close to the previous transaction price. These traders are supposed to show less biases, to use different information sources and to possess more accurate information about the to-be-predicted outcome than non-marginal traders. However, Forsythe et al. didn’t measure these constructs and their influence on information aggregation directly but rather inferred their role from observing the trading behaviour of market participants.

1.2.5 Critics of the Predominant Theory

Further empirical research by other scholars has not shown any presence of unbiased “marginal traders” in prediction markets (Beckmann & Werding 1996, Bruggelambert 2004). Furthermore, it is improbable that a minority of traders can outweigh the market power of all other investors simply through trading and therefore fully account for the information aggregation efficiency.

1.2.6 Alternative Model of Information Aggregation

Therefore, in this thesis, the predominant theory of marginal traders will be challenged by analyzing the underlying assumptions regarding marginal traders with an improved experimental design. The new experimental will test the relationship between trader type, choice of information source, presence of biases and information accuracy. By this way, it should be verified directly whether these factors determine individual information accuracy and therefore can be attributed to determine aggregate information efficiency.

This research seeks to measure the constructs directly through questionnaires and to show that they cannot explain information aggregation efficiency in markets solely. It should be shown that

information aggregation efficiency depends rather on global market characteristics than individual trader characteristics.
An alternative theory of information aggregation that supposes the double auction to act like an averaging mechanism is discussed and empirically tested. The alternative model accounts allocative efficiency measured by competitive price level as well as supply and demand structure as determinants of information aggregation efficiency.

1.3 Research Objective

The objective of this thesis is to identify determinants of information aggregation in markets in order to achieve higher prediction accuracy in practice through improved market design and improved interpretation of market results

By proposing an alternative model of information aggregation that accounts allocative efficiency as well as supply and demand characteristics for efficient information aggregation a new theoretical model will be contributed.

In addition, an existing predominant model that accounts the presence of a specific type of trader, called marginal trader, as a determinant for efficient information aggregation will be challenged.

1.4 Research Questions

The following questions will be answered in order to challenge the predominant theory of information aggregation that account trader type as:

Q1:	Do trader types in prediction markets differ in terms of individual information accuracy?

Q2:	Do trader types in prediction markets differ in the sources of information they use?

Q3:	Do trader types in prediction markets differ in terms of presence of biases that affect information processing and selection?

The following questions will be answered in order to test the proposed alternative model of information aggregation and its determinants:

Q4:	Does the level of price competitiveness affect information aggregation in prediction markets?

Q5:	Does the supply and demand structure affect information aggregation in prediction

markets?

Q6:	How can competitive price levels and supply & demand structure be measured in prediction markets?

1.5 Research Methodology

This master thesis will be organized as follows. First, a literature review will be conducted in chapter 2. Some relevant concepts from existing research into prediction markets and from research into the fields of experimental and neoclassical economics, efficient market theory and statistical psychology will be discussed and conclusions drawn.

A predominant theory of trader-based information aggregation in markets will be presented and alternative hypotheses regarding the underlying assumptions will be formulated. Based on some empirical findings in previous research, an alternative model of information aggregation which considers allocative afficiency and demand and supply structure as determinants will be described in chapter 3.

The assumptions of both models will be tested with an own set of prediction market experiments. Resulting datasets will be analyzed with quantitative statistical methods and interpreted. Depending on the empirical results, the alternative model will be adjusted or rejected.

2 Literature Review

2.1 Efficient Information Aggregation in Markets

It has already early been proposed by von Hayek (1945) to use market mechanisms for the purpose of efficient information aggregation and decision making. During the first half of the 20th century, markets had been implemented successfully to generate accurate forecasts and have reached levels of liquidity and market size that have never been reached again since then. Between 1868 and 1940, prediction markets were run during 15 presidential elections on the New York stock exchange (Rhode & Strumpf 2003). During that period, the final market price predicted the final election outcome only one time inaccurately. The prediction accuracy observed in historical prediction markets is even far more astonishing given the fact that information propagation occurred very slowly at that time. News spread usually by telegraphic transmission and appeared only several days later.

Comparable levels of prediction accuracy have been reported for a number of electronic prediction markets over the last decade. Table 2.1 summarizes some of those results.

Table 2.1

Author	To-be-forecasted event	Contract Type[2] (currency)	Participants	Markets	Accuracy
Chen & Plott (2002)	(Sales forecasting at Hewlett Packard)	spread (real money)	7-26 per market	12	MAFE[3] = 0.24 (performed better than institutional expert forecast in 6 out of 8 markets)
Spann & Skiera (2003)	Play money	Spread (play money)	725,000 registered participants	152	MAFE = 0.31
Rhode & Strumpf (2003)	Historical elections	Index (play money)	N/A	15	Predicted winner in 14 of 15 election accurately
Berg et al. (2000)	US presidential elections	Index (real money)	N/A	5	MAFE = 0.013

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[2] for a detailed explanation of contract types see chapter 2.20.

[3] percentual mean average forecast error

	Other electoral US	index (N/A)	N/A	14	MAFE = 0.034
	Non-US elections	Index/other (N/A)	N/A	30	MAFE = 0.021
Gruca et al. (2005)	Movie box office forecasts	spread	34-111 per market	11	MAFE = 0.29
Chen et al. (2005) Servan-Schreiber et al. (2004)	NFL matches (NewsFutures)	binary	960	142	MAFE = 0.38
	NFL matches (TradeSports)	binary	50-200	137	MAFE= 0.40
	NFL matches (ProbabilitySports)	binary	50-200	144	MAFE= 0.364

It can be seen from the results that electoral results are predicted much more accurately than sports events. This can be explained by the higher inherent predictability of elections. More relevant and pertinent news such as opinion polls and television debates are available that help traders form accurate predictions.

What exactly makes prediction markets to work so accurately remains a mystery. Wolfers and Zitzewitz (2004) argue that the success of prediction markets arise from the fact that they provide incentives for truthful revelation, information research and discovery and an algorithm for aggregating opinions. However, this explanation is not satisfying by itself.

2.2 Efficient Market Hypothesis

Markets have always been known as suitable institutions for achieving efficient allocation of goods and financial assets. Therefore, it seems plausible to assume them to be a suitable mechanism for allocation of information in the rising information age as well. It is therefore not surprising to read authors citing efficient market hypothesis as an explanatory model for efficient information aggregation in markets (Wolfers & Zitzewitz 2005a). Efficient market hypothesis states that all available and relevant information about an asset in a financial market is reflected in its market price (Fama 1970). According to this theory, if new information is made available, the market price tends to adjust so quickly that one cannot obtain any profit from trading insider information.

Thaler et al. (1988) suggested using betting markets as a model to investigate and explain efficient market hypothesis. Betting markets share many characteristics with prediction markets.

Both provide an excellent environment for testing efficient market theory. This is especially due to the determined contract specifications and market settings in both market types. For instance, a financial market asset like a share is traded on an infinite scope and there are multiple definitions of the underlying asset value, leaving room for different interpretations of market price. In contrast, a contract in an electoral prediction market is traded on a definite outcome that has a clearly observable state on a certain date.

Classical capital market theory as propagated by Fama (1970) states that markets require fulfilling four conditions to achieve efficiency:

The first condition concerns violations of arbitrage free pricing. Efficient capital markets require that nobody can profit from simultaneously trading the same contract. For the case of prediction markets, this means that nobody should be able to trade the same contract at different prices in different markets at the same time.

The second condition concerns the use of historical price information for building trading rules. In efficient markets, it should not be possible to infer future contract prices from historical data.

The third condition concerns the possibility of making trading profits based solely on publicly available information. It should not be possible to make trading profits based on common information.

The fourth condition concerns the possibility of making trading profits based on private information. This condition is rarely met in prediction markets as it would require all knowledgeable individuals in the world to contribute their information to the market by trading activity in order to guarantee a sufficient level of market efficiency.

Observed evidence from prediction markets suggests that markets which failed to meet the mentioned requirements can achieve a high level of prediction accuracy anyway. For instance Chen and Plott (2002) observed in 12 markets for sales forecasting a violation of the non-arbitrage condition. In markets with small number of participants and little liquidity the no-arbitrage condition is often violated. Despite this type of inefficiency the market performed quite well in comparison with institutional expert forecasts. However, the occurrence of measurable no-arbitrage violations in prediction markets does not necessarily mean that traders could profit from arbitrage opportunities as this usually requires a certain degree of market liquidity. The mere fact that market prices that occurred in the past theoretically allow arbitrage does not mean that transactions can be immediately executed at that price as this depends usually on demand and supply situation.

It remains to this date unknown to what extend the level of market efficiency affects information aggregation in markets. It has been shown that even prediction markets with a high number of traders tend to show violations of one or more conditions of market efficiency without forfeiting information aggregation efficiency (Oliven & Rietz 2004)

2.3 Trader Type

Forsythe et al. (1992) use the efficient market theory as a framework to explain the accurate forecasting results of presidential elections that have been observed in the Iowa Electronic Markets (Forsythe et al. 1992, Oliven & Rietz 2004) and the University of British Columbia political markets (Forsythe et al. 1998). The authors found that although most traders in the market showed biases the aggregated market price served as a highly accurate prediction metric. They found evidence for the presence of a particular minority group of traders in those markets, called “marginal traders”. These traders frequently submit limit orders at prices close to the market price, make higher investments and achieve higher trading returns than non-marginal traders. Forsythe et al. claim that these traders show less biased and more rational trading behaviour. However, this theory opposes another predominant economic theory which assumes all individuals to follow a concept of bounded rationality in which individuals usually exhibit at least partly non-rational behaviour (Simon 1955).

According to the theory of “marginal traders”, biased and uninformed traders tend to push the market price through their trading behaviour towards an inaccurate level. But at the same time, these deviations from the accurate price serve as incentives for marginal traders to enter the market and to benefit from trading. Forsythe el al. (1992) argue that marginal traders drive the market price towards a more accurate predictive level. Marginal traders are often referred to as “market makers” because they are thought to place the best outstanding bid and ask orders at prices that are accepted by biased traders (also referred to as “price takers”) subsequently.

2.4 Critics of Marginal Trader Hypothesis

While many authors in the field cite the theory of marginal traders as explanation for the efficient information aggregation in prediction markets few have raised doubts and have sought to address this issue with further research and empirical evidence. For instance, other authors conducted analysis of data from several German political stock markets using the framework of Forsythe et al. but found no evidence for the superior rationality of marginal traders. Marginal traders in these markets did not systematically purchase shares of true favourites but preferred to buy share of candidates for which showed a preference as well regardless of their true winning chances (Bruggelambert 2004, Beckmann & Werding 1996).

James Surowiecki (2004), author of an influential bestseller book in the field, stimulated a controversial debate by opposing the marginal trader theory. As he put it out:

"The idea of the 'marginal investor' … is an intuitively appealing concept, because it allows us to retain our faith that a few smart people have the right answers while still allowing the market to work. But it's a myth. There's no marginal investor in the sense of a single investor (or a small group of investors) who determines the prices that all investors buy and sell at. No trader … has enough capital to outweigh the aggregated buying and selling power of all the other investors."

2.5 Source of Information

Forsythe et al. (1992) suggested that marginal traders differ from ordinary traders in that they are able to recognize when news happens and when not. They measured reactions to news events prior to the elections by comparing upper percentile price changes after important news occurred and trading behaviour of market participants.

Berg and Rietz (2005) claim that information structure with regard to public and private information may affect prediction accuracy of markets. The results of their ongoing research are still not available but their survey results show that only 76% of the market participants reported basing their trades in at least 50% of cases on information. The question is how traders who base their trading decisions and probability judgments on different sources of information such as news, expert judgments or intuition perform relative to other traders in terms of trading success and prediction accuracy and how such sources affect prediction accuracy.

There are some concerns the informational success of prediction markets might derive from external information aggregation mechanism like polls or betting markets in the case of sports prediction markets. However, two arguments violate against this assumption. First, Forsythe et al. (1992) could show by a regression analysis that market prices in the Iowa Presidential Markets did not follow poll results but anticipated them. Second, it would not explain why prediction markets achieved better prediction accuracy than polls in most cases.

2.6 Monetary Incentives and Transaction Costs

However, if we assume the marginal trader hypothesis to be valid, then transaction costs would seriously affect the attractiveness for marginal traders to enter the market as they would impede those traders from benefiting from marginal gains. Tradesports[4] and NewsFutures[5] are two main public prediction markets that offer similar contracts to bet on NFL football game outcomes. While NewsFutures charges no trading fees TradeSports charges different trading fees for "market makers" and "price takers" to stimulate marginal trading behaviour. Those traders who set an outstanding bid with limit price that is not immediately executed ("market makers") are

[4] http://www.tradesports.com

[5] http://www.newsfutures.com

charged no trading fees. Those traders who accept the best outstanding bids (“price takers”) and whose orders are immediately executed are charged commission fees.

Despite these differences Servan-Schreiber et al. (2004) found no significant differences in forecast accuracy between the two markets. These evidences raise some doubts about the role of marginal traders.

The authors suggest an alternative explanation for the similar performance of both markets. They differ between intrapersonal and interpersonal opinion weights in the information aggregation mechanism that might affect market performance and argue that these effects counterbalance each other. Newsfutures endow all its participants with the same initial amount of play money and is therefore thought to weight interpersonal beliefs stronger. TradeSports in turn is thought to stimulate people to better assess their betting risk due to the use of real money, thus weighting intrapersonal beliefs stronger.

2.7 Biases and Knowledge

Following their findings that showed no difference between real-money and play-money markets, Servan Schreiber et al. argue that knowledge and motivation must be the most important factors to explain accuracy in prediction markets and think real-money incentives to be of secondary importance. Kambil and van Heck (2002) argue that participants of markets “must represent the peer group that is knowledgeable about the issues the market seeks to address”. However, no further explanation regarding these assumptions is provided.

One might also ask for the role of information processing capabilities of participants. Besides collecting and possessing all relevant information it is crucial to select and interpret this information in the right way to form accurate assumptions about future outcomes. Researchers in the field have shown the presence of biases and irrational behaviour among traders in prediction markets. Forsythe and al. (1999) have found evidence for the presence of assimilation-contrast bias among traders. The prediction of future outcomes by participants was found to be significantly influenced by their own preference for that outcome.

2.8 Diversity of Agents

Hong and Page (2004) conducted laboratory experiments with artificially programmed agents that mimic human agents and that use diverse heuristics with different levels of ability for problem-solving tasks. The authors found evidence that groups of low-ability agents with diverse heuristics outperform same-size groups of high-ability agents that use homogeneous heuristics. They found a trade-off between high-ability and diversity of agents but conclude that an ideal group will be composed of agents with both high-ability and diversity.

Hong and Page (2004) argued that with increasing size, a group will get automatically more diverse, thus supporting observations from opinion pools which performed better with increasing size up to a certain number of participants (Chen et al. 2005). Hong and Page argue that the value and contribution of an additional agent for the group performance depends not so much on his problem solving ability but on his heuristic approach relative to other problem solvers. Based on these findings and in context with prediction markets, one may raise the question whether markets with biased participants may not achieve high information aggregation efficiency collectively. Therefore, the crucial question may not be whether biased or unbiased participants are in the market but whether biases are diverse.

However, Hong and Page (2004) content that the model did not consider communication costs and learning. They argue that groups with agents having different perspectives may lead to higher communication costs between agents. One advantage of market mechanisms is that it allows participants to communicate via and learn from uniform price signals thus reducing communication costs and facilitating information aggregation.

2.9 Price Signals and Learning

Bondarenko and Bossaerts (2000) developed and tested a model of Bayesian inference to show with data from the Iowa Electronic Market that participants are following Bayes' law in learning from signals and updating constantly their beliefs. They conclude that participants have initial beliefs about the conditional probability of future events. For instance, a participant who bets on the outcome of an election may estimate the likelihood of victory for a particulate candidate as 60% if he performs well on the next TV debate and 35% if he performs worse. The final estimation finally depends on a signal (in this case the performance of the candidate during the TV debate). In a market, prices can serve as signals for individuals to update their beliefs.

Gruca et al. (2005) could provide further evidence for this theory by showing that price signals let participants adjust their beliefs towards a market consensus. Rhode and Strumpf (2003) observed in historical electoral prediction markets that the contract prices often started at levels close to even odds and then converged to higher or lower price levels later if the margin of a candidate was wide. They hypothesized that traders anticipate news to occur that forces them to alter their predictions later. The logical conclusion is that the most accurate information should be contained in the last trading prices prior to occurrence of the to-be-predicted event. However, it has also been shown that individuals are prone to the hindsight bias. This bias describes the tendency of individuals to overweight the informational relevance of new information in contrast to prior information (Davis & Holt 1992).

Therefore, Gruca et al. (2005) pointed out that it may be crucial to collect private information prior to any market activity in order to get an impression of the trader's private information. When such private information is collected later after beginning of market activity it may be influenced by information from other traders through price signals and thus represent public information.

2.10 Averaging Principle

A quite robust explanation for the mechanism of information aggregation in information markets stems from the field of statistical psychology. A multitude of experiments conducted in the first half of the 20th century by experimental psychologists showed that average judgments from members of large groups often outperform the best individual judgment, even if individuals were much more skilled (Larrick & Soll, 2006). A simple statistic phenomenon called “averaging principle” may explain the superior performance of prediction markets compared to individual experts. The averaging principle simply cancels out errors of individual estimates by building the arithmetic mean of estimations from several individuals. However, to benefit from this mechanism individual estimations need to be symmetrically distributed around the true value to be estimated (also referred to as “bracketing”).

2.11 Opinion Pools

Much evidence from prediction markets supports the hypothesis of the “averaging principle” as mechanism of price formation. Chen et al. (2005) conducted an empirical comparison of prediction stock markets (TradeSports, NewsFutures) and an opinion pool (ProbabilitySports[6]). The authors showed that the opinion pool market performed not significantly different compared to the two prediction stock markets in terms of forecast accuracy. They showed furthermore that the simple arithmetic average of opinions in opinion pools provides the best prediction metric. Therefore, we may conclude that the information aggregating mechanism in markets acts like a simple averaging mechanism as well.

Opinion pools like ProbabilitySports are often referred to as “expert judgement” pools and compared as a different information aggregation institution to prediction markets (Servan-Schreiber et al. 2004). However, participation in ProbabilitySports is allowed to every participant who pays a small entry fee and not just to a distinguished group of experts. We may reasonably ask whether an opinion pool like PropabilitySports might not be a kind of market itself despite the lack of a trading system and a lacking interaction among participants. ProbabilitySports encourages its participants to provide their private information for incentives that depend on their level of accurate predictions in turn. In contrast to classic opinion polls, participants in opinion pools are encouraged to reveal probability estimations of future outcomes instead of preferences.

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[6] http://www.probabilitysports.com

2.12 Probability Elicitation

The problem of estimating probabilities is that individuals have often not sufficient experience in estimating probabilities as probability distributions cannot be observed directly in reality. Scoring rules help to elicit true probability judgments of individuals by tying a payoff to a function of the estimate (Davis & Holt 1992). Such a function measures the difference between the estimated probability distribution and the true observed distribution.

One example of such a function is the quadratic scoring rule in the setting of binary to-be-predicted outcome.

Payoff = $1 - (r - I)^2$ where I is a binary variable representing the true outcome and r is the probability estimate. If the individuals want to maximize their payoff function they need to state the true probability estimate. The lower the absolute difference between predicted and observed distribution the higher will be the payoff. Such a reward function was also utilized in the case of ProbabilitySports.

2.13 Market Price and Averaging Principle

Wolfers et al. (2005b) and Gjerstad (2004) set up different formal models showing the market price in stock markets to be very close to the mean of market participants' beliefs if the distribution of beliefs is symmetric. Gjerstad argues that the distribution of traders' beliefs may affect price formation in prediction markets. However, he contents that in the case of logarithmic utility function market prices will usually equal to the mean of traders' beliefs independent of the distribution of beliefs. Wolfers et al. (2005b) could find empirical evidence for his theoretical model in data from the opinion pool ProbabilitySports. It is therefore not illegitimate to conclude that the market mechanism and its resulting market price work in prediction markets as an algorithm that averages the beliefs of market participants.

However, Manski (2005) shows in his formal model that market price can diverge from the mean of beliefs. His model assumes risk-neutral market participants and he argues that the level of risk preference among traders does not influence price formation but rather influences the part of budget invested. All these models differ in that they are based on restrictive assumptions. Some models assume risk-averse traders with different levels of risk-aversion, some assume risk-neutral traders, some assume equal utility functions for all traders, some use wealth-weighted means (so that beliefs of traders with a higher wealth are weighted more) or non-wealth-weighted. It is unlikely that the information aggregation mechanism behaves in such an uniform manner and these models omit one import feature of prediction markets. The ability to learn from the belief of other traders through price signalling, which is difficult to express within a formal model. However, prediction markets may stimulate information exchange and adaptation of individual beliefs and finally result in a market price that represents the mean of modified beliefs.

Gruca et. al (2005) support the idea of an averaging mechanism accounting for information aggregation efficiency with further evidence from laboratory experiments in which they showed that the mean of initial individual predictions from market participants highly correlated with the mean implied by final market prices. The authors observed a tighter distribution of forecasts around the consensus in the market compared to the initial situation and concluded thus that markets help groups to reach a consensus.

Van Bruggen et al. (2006) found similarities between the information aggregation mechanism of the Delphi forecasting technique and prediction markets. In the Delphi approach, experts share their forecasts iteratively and anonymously until a consensus is reached. However, the method lacks some important features like an incentive mechanism that fosters truthful revelation, information research and frequent updating as one find it in prediction markets.

2.14 Aggregate Uncertainty

The success of prediction markets depends critically on whether the prediction situation shows aggregate uncertainty. Aggregate uncertainty occurs if an event cannot be predicted with a certain level of confidence based on the aggregated fragments of information collected from informants. Chen et al. (2006) posit that in markets without aggregate uncertainty, the best prediction is reached through a direct communication equilibrium. That is, if all traders communicate their private information directly to each other so that an equilibrium can be reached which represents the best informed prediction with which all traders can agree. However, Chen et al. claim that in the case of aggregate uncertainty, such an equilibrium must not necessarily be reached.

2.15 Knowledge Heterogeneity

Van Bruggen et al. (2006) differ between forecasting situations with high and low knowledge heterogeneity. They posit that low knowledge heterogeneity occurs if informants have access to public information and don’t differ much in their beliefs while high knowledge heterogeneity is believed to occur if the to-be-predicted event has a high inherent uncertainty and beliefs differ much among individuals. The authors refer to the prediction of financial indicators or sales forecasts within a team of sales persons as a forecasting problem of low heterogeneity while the prediction of sports events or new product success is believed to belong to a high heterogeneity forecasting problem.

Van Bruggen et al. (2006) identified four factors to distinguish between different levels of knowledge heterogeneity. The first includes the presence of an anchor point for the prediction. Forecasting problems that have a strong anchor point for building the forecast (e.g. the superior past performance of a soccer team that lets informants judge the probability of future victory higher). The second includes the amount of public vs. private information. The third includes the inherent predictability and the fourth including environmental variability.

Van Bruggen et al. (2006) compared the forecasting performance of key informants, prediction markets and opinion pools (which they refer to as combined judgmental forecasts). They found that prediction markets performed better than combined forecasts and key informants in high heterogeneity forecasting problems such as predicting the winner of soccer plays. In forecasting situations with low knowledge heterogeneity, namely the prediction of financial indices, no forecasting mean dominated the other in terms of prediction accuracy. However, if sports events are thought to show high knowledge heterogeneity then it remains unclear why Chen et al. (2005) found no significant difference in prediction accuracy between prediction markets and combined forecasts in predicting sports events. Also, the level of heterogeneity may vary considerably among different sports forecasting situations and may not solely be determined by the nature of the to-be-predicted event.

2.16 Number of Traders and Informants

The paradox that was mentioned in the last section may be explained by the different number of traders in the markets analyzed by Chen et al. (2005) and van Bruggen et al. (2006). While the number of informants and traders in the prediction markets and opinion pools analyzed by van Bruggen et al. was held constant at 6 traders per market, the prediction markets and opinion pools analyzed by Chen et al. (2005) attracted often more than 100 traders.

Hansen (2003) noted in this context the superior ability of markets in pooling information from many individuals. According to the author, pooling mechanisms work well or even better than prediction markets when the number of traders is low or equals only one informant. However, with an increasing number of informants he supposes markets to do a better job in selecting and aggregating complementary pieces of information. Most pooling mechanisms simply average different pieces of information from different informants. These information fragments may have different degrees of completeness and relevance so that information may get lost through simple averaging. However, the results observed in the analysis by Chen et al. (2005) and van Bruggen et al. (2006) seem to rebut this theory as the sports forecasting markets performed only significantly better than combined forecasts in the case of few participants but not in the case of hundreds of participants.

Van Bruggen et al. (2006) posit that markets with only a small number of knowledgeable participants tend to show less information aggregation efficiency. This assumption is contrary to the marginal trader paradigm which posits that prices are determined by knowledgeable traders regardless of their relative or absolute ratio of the trader population.

2.17 Self Selection vs. External Selection

It is noteworthy to make a little objection here. Chen et al. (2005) acted on an analysis that was performed and published earlier by Servan-Schreiber et al. (2004). In this analysis, Servan-Schreiber et al. found a slightly significant advantage for prediction market compared to opinion pools in terms of forecasting accuracy although they used the same data as Chen et al. (2005).The reason for this paradox is that the analyzed opinion pool, ProbabilitySports, forced all its informants to make a forecast for every game of the NFL season and automatically added a value if the informants did not themselves. Chen et al. (2005) excluded these artificially added forecasts from analysis and then found no difference between the opinion pools and the prediction markets anymore. Here lies the reason why many scholars like Hanson (2003) question the efficiency of the opinion pooling mechanism. In markets, informants select themselves according to the knowledge they can add to the already contributed knowledge represented by the market price.
However, self-selection must not necessarily lead to contribution of more accurate information. 89% of the traders that participated in the Iowa presidential markets reported they believed that they were more informed about the election than their peers, thus showing a substantial overconfidence bias (Berg & Rietz 2005). Therefore, we cannot simply assume self-selection to work as the key element of efficient information aggregation in these markets.

There have been numerous attempts to increase the forecast accuracy of opinion pools by weighting the opinions of informants. However, Chen et al. (2005) and van Bruggen et al. (2006) did not find any improved forecast accuracy for prediction metrics with weighted opinions. There were rarely any key informants who outperformed the mean forecast on average for a set of different forecasts.

2.18 Market Making Mechanism

Another objection has to be made. Van Bruggen et al. (2006) used a market making trading mechanism that differed from the one used at other prediction markets like TradeSports and NewsFutures. The trading mechanism was designed according to the combinatorial markets rule suggested by Hanson (2003). This rule allows traders to trade a contract any time at previously determined price. It combines the advantages of opinion pools with an integrated scoring rule in markets with a low number of traders with those of markets if a sufficient number of traders are present. The mechanism increases the market price for each new buy order and decreases it for each new sale order according to an adjustment rule. Each trader pays off the trading partner of the previous transaction in which he was involved while the market owner pays off only the trader of the last transaction. There is no order queue and simultaneous auction like in the double auction mechanism used in markets like Tradesports or NewsFutures. In markets with low liquidity, such market making mechanism will stimulate trading and thus market efficiency.

However, the double auction mechanism may hold superior outcomes in markets with high liquidity, as suggested in the next chapter.

2.19 Double Auction Market Mechanism

Since Chamberlain's first classroom experiments with double auctions in (Chamberlain 1948) many efforts have spent to investigate this type of market mechanism which showed high efficiency in reaching competitive outcomes. The major advantage of double auctions compared to other market institutions is that bidding processes of buyers and sellers occur simultaneously and in a decentralized manner. Bidders submit either a sell order at a limit price (bid) or a buy order at a limit price (ask). Trades usually occur at prices somewhere between limit ask and limit bid prices if the bid (or ask) price of the submitted order matches the ask (or bid) price of the best outstanding order depending on the trading mechanism. If the bid or ask price of a submitted order doesn't match the ask (or bid) price of an existing order the order will be added to a queue.

A typical characteristic of such markets is that prices converge quickly towards the efficient equilibrium (Davis & Holt 1992). It should be noted that this definition of market efficiency, which stems from the field of microeconomics, differs from the definition provided by capital market theory and discussed earlier. The definition from microeconomics refers to an allocative efficiency where no additional surplus in buyer or seller rent can be extracted from further trading. In terms of pareto efficiency, allocative efficiency equals an equilibrium where no trader can gain higher benefit through trading without decreasing the benefit of another trader. In other words, the equilibrium price represents an optimal "information consensus" among all market participants or a forecast to which everyone can agree to some extend.

Gode and Sunder (1993) showed in a set of experiment with programmed "zero-intelligence" traders in artificial computer markets even don't need to have experienced or educated traders present to achieve efficient outcomes. This is in contrast to the view of Forsythe et al. (1992) and other scholars who account the presence of experienced traders in markets as key to efficient markets and successful information aggregation.

However, we need to differ between allocative efficiency and information aggregation efficiency. It remains unclear how allocative efficiency really affects information aggregation efficiency.

2.20 Contract Types

Wolfers and Zitzewitz (2004) distinguish between three contract types designed to estimate target quantities or probabilities in prediction markets. Winner-takes-all contracts (also referred to as binary contracts) pay out a certain payoff if a certain outcome y of an event occurs and nothing in the case of the opposite outcome. The reservation price a trader is willing to pay for the contract at a certain time prior to the event thus represents the final payoff times its expected probability (e.g. winning chance of a particular soccer team).

Index contracts (also called linear contracts) pay out a payoff tied to the index value that is directly linked to the outcome of an event (e.g. election vote share of a party)

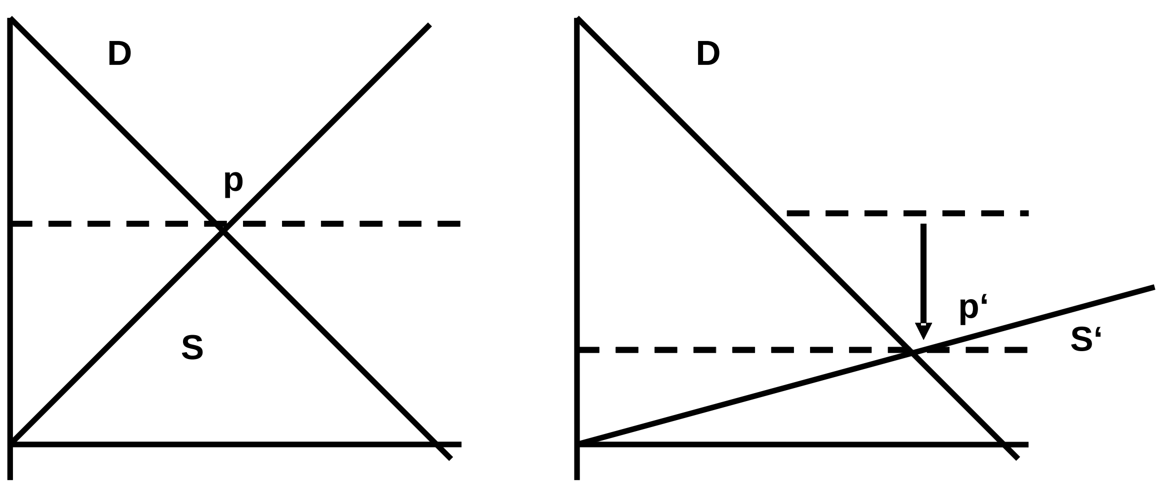
The respective reservation price a trader is willing to pay for such a contract therefore corresponds to his estimate of the expected index value.

Spread contracts pay out a payoff if the to be predicted value falls within a mutually exclusive set of ranges or above a threshold value (e.g. box office revenues for a film will be between 100 and 125 Mio. Dollar.)

2.21 Supply and Demand Structure

With knowledge of the marketer's reservation prices it is possible to depict supply and demand curves. In goods markets these reservation prices are determined by cost and value of goods. In prediction markets reservation prices must correspond to the perceived value of the traded security which is tied to the outcome of a future event. This value is in turn determined by the traders' probability estimation.
If supply and demand curves are symmetric with a falling demand curve and an increasing supply curve they intersect exactly in the midst between reservation bid and ask values. In the setting of a symmetric prediction market, the resulting equilibrium price then represents a mean of individual's probability estimations (see Fig. 1 left hand). In fact, demand and supply structure reflects the distribution of traders' beliefs.

Figure 2.1: Equilibrated Supply (S) & Demand (D) structure and Information Averaging



The price formation mechanism of double auction markets could thus explain the similarities found among opinion pools and prediction markets as observed by Gruca et. al. (2005). However, in the case of asymmetric markets or box-shape curves, trading prices often form above or below the average of reservation prices depending on the elasticity of the demand or supply curve (see Fig. 1 right hand and Fig. 2). This raises inevitably the question whether such prices have lower prediction accuracy compared to predictions formed by averaging.

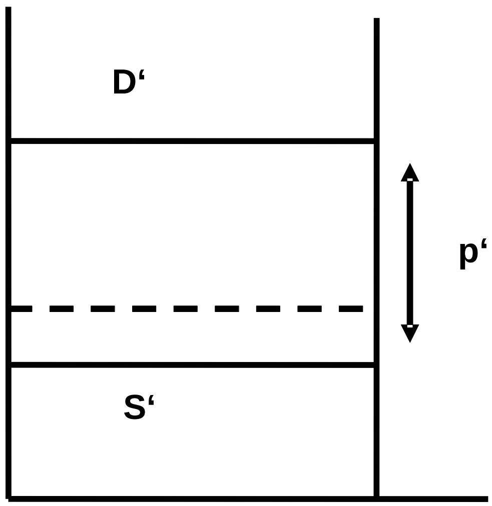


Figure 2.2: Box-shape Demand (D’) and Supply (S’) Structure with Non-determinable Equilibrium Price

2.22 Allocative Efficiency and Competitive Prices

Vernon Smith (1962) observed that after sudden shifts in demand and supply it took more time and number of trades to reach competitive price levels again. Such shifts must occur quite often in prediction markets if new information about the underlying event of an asset is becoming available and is updated.

Smith provided performance indicators to measure the market efficiency with regard to competitive equilibrium like the ratio of possible rent surplus obtained by traders and the coefficient of price convergence. The ratio of possible rent surplus measures which percentage of the total buyer and seller surplus (the difference between reservation prices of traders and the actual trading prices times the quantity) was obtained through trading. The coefficient of price convergence measure the mean divergence of the real transactions prices from the hypothetically constructed equilibrium price which represents an ideal situation of optimal efficiency. An interesting question is whether such performance indicators might indicate the competitive outcome and accuracy of prediction markets ex ante.

3 Conceptual Framework

3.1 Introduction

The conceptual model of this thesis is composed of two parts:

The first part 3.2 is devoted to restate the conceptual model that is inferred from the existing trader-based model of information aggregation by Forsythe et al. (1992) with different hypotheses regarding the relationship of independent and dependent variables.

The second part 3.3 is devoted to form a new theoretical model based on results of the literature review.

3.2 Conceptual model (Part I) – Trader-based Model of Information Aggregation

As discussed in chapter 2 the trader-based model of information aggregation by Forsythe et al. (1992) is currently the most cited and commonly used model. Central to its paradigm is the presence of a certain type of traders in the market, called “marginal”-traders. These traders are assumed to show less biases and to be able to recognize relevant information in opposite to non-marginal traders. Marginal traders are supposed to determine market prices and are therefore assumed to be responsible for efficient information aggregation in prediction markets. Marginal traders can be identified by their trading behaviour as they usually submit orders close to last trading price that are matched subsequently by other (non-marginal) traders.

3.2.1 Presence of Biases

Forsythe et al. (1992) observed that non-marginal traders who indicated a preference for a certain outcome (e.g. election of a candidate) tended to hold more assets related to that outcome and tended to pay higher prices for such assets. They inferred from that observation that these traders would overestimate the likelihood of that outcome and make less accurate predictions, a bias known as contrast-assimilation bias. They concluded that these traders cannot account for the accurate predictions obtained by the aggregated market result (market price) and that, thus, marginal traders must contribute all accurate information to the market through their trading behaviour.

In the classic model, the presence of biases is therefore assumed to depend on trader type and to affect individual information accuracy. As discussed in the literature review, several researchers did not confirm such a relationship. Therefore, in our revisited model, we hypothesize a non-existent relationship of trader type and presence of biases:

H1: Marginal traders do not show a higher presence of contrast-assimilation biases than non-marginal traders

The construct of presence of contrast-assimilation biases can be measured by inquiring traders about their preference for a securities' related outcome. It is expected that individuals exhibiting a bias should indicate a clear preference for either soccer team A or B. The utilized experimental setting will include a questionnaire that is submitted together with each order and that asks traders indicating either a preference for a soccer team or no preference.

3.2.2 Choice of Relevant Information and Relevant Information Sources

Forsythe et al. (1992) analyzed the trading behaviour of marginal traders with regard to the occurrence of major news events during the market course. They found a relationship and inferred that marginal traders must be better in recognizing accurate information via news. However, that construct wasn't tested directly.

Following the previous line of reasoning with the lack of empirical evidence, we hypothesize that there is no such relationship:

H2: Marginal and non-marginal traders do not differ in their choice of information sources

The construct information source will measured through a questionnaire that is provided together with the order screen and asked to be filled out for every order.

3.2.3 Conclusion

Fig. 3.1 depicts the assumptions. In contrast to the predominant model of information aggregation, it is hypothesized that the type of trader will not differ in the presence of contrast-assimilation biases implied by indicated preferences and neither in the utilized sources of information.

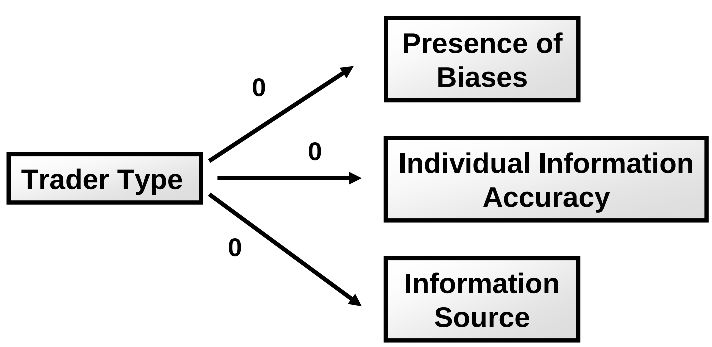


Figure 3.1: Trader-based Conceptual Model

Furthermore, we hypothesize that there are no differences in individual information accuracy between different trader types.

H3: Marginal and non-marginal trader do not differ in terms of individual information accuracy.

The construct of individual information accuracy will be measured through a questionnaire which asks people to estimate the probability of the event that is related to the security traded in the market. Afterwards, the mean absolute forecasting error can be compared for each trader.

3.3 Conceptual model (Part II) – Market-based Model of Information Aggregation

As discussed in the literature review, experimental economists have identified several determinants of market efficiency that affect price formation in double auction markets. Based on the findings of Smith (1962), a new model of information aggregation that considers allocative efficiency and equilibrated supply/demand structure as determinants. As noted in the literature review, statistical averaging is an information aggregation mechanism that has been shown to achieve the same prediction accuracy as double auction markets. In addition, Gruca et al. (2005) showed empirical evidence that the mean of private information (individual probability estimates) among market participants tends to converge to the market price. It is therefore logical to conclude that the double auction mechanism averages information of market participants as well.

3.3.1 Supply and Demand

In double auction markets, demand and supply curves correspond to the set of individual reservation prices in conjunction with demanded or offered quantity. In a prediction market, these reservation prices must logically correspond to probability estimations of the asset's underlying future event in conjunction with demanded or offered quantity. If supply and demand curves are symmetric and are neither completely inelastic nor completely elastic they will intersect exactly at the average of all reservation prices. The competitive market price level p will then correspond to the average of all traders' probability estimations or the average of all traders' private information. Fig 3.2 (left side) depicts this situation. The points on the demand curves correspond to a set of probability estimations ($\theta^i_1,\ldots, \theta^i_n$) for the contracts' underlying event i by all traders. The points of the supply curve correspond to the probability of the contracts' underlying opposite event k.

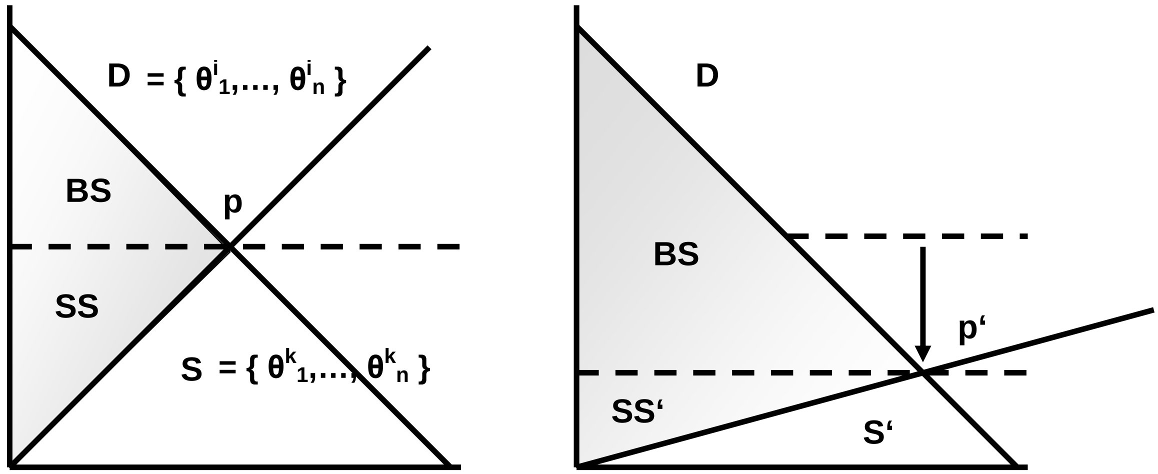


Figure 3.2: Equilibrated supply & demand structure leads to information averaging

However, if the are strong demand and supply imbalances that lead to a non-equal ratio of buyer (BS) and seller (SS') surplus the competitive price level will be above or below the average of all probability estimations (see Fig. 3.2 right side). In such cases we should observe a lower prediction accuracy and a deviation from the mean of individuals' probability estimations.

H4: Markets with asymmetric supply and demand structure generate prices with lower prediction accuracy

The construct of supply and demand structure will be measured with a coefficient of buyer/seller surplus ratio as described by Smith (1962).

3.3.2 Allocative Efficiency and Competitive Price Level

For the new model, we hypothesize that, given symmetric supply and demand curves, only competitive prices correspond to the average of private information. Consequently we should observe prices with less accurate predictive information if prices diverge from the competitive equilibrium.

H5: Markets with non-competitive prices achieves lower information accuracy

The construct of competitive price level can be measured with a coefficient of price convergence as described by Smith (1962).

3.4 Conclusion

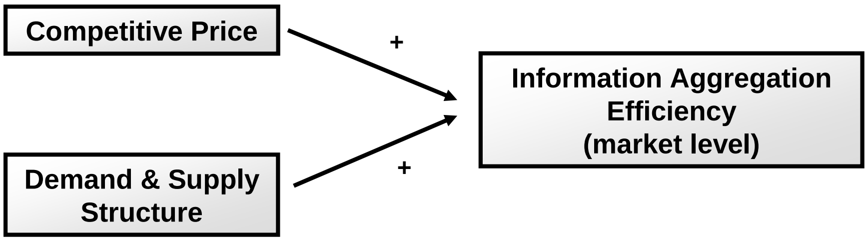


Figure 3.3: Conceptual model of market-based information aggregation

Fig. 3.3 depicts the new conceptual model of information aggregation which considers determinants of market efficiency.

A competitive price level and symmetric demand and supply curves with an equilibrated ratio of buyer and seller surplus is assumed to positively influence information aggregation efficiency on a market level. Information aggregation efficiency is measured through prediction accuracy of the market price. The model assumes that other factors are controlled through the experimental setting and are not supposed to influence information aggregation efficiency significantly.

4 Experimental Design & Research Methodology

4.1 Introduction

The following chapter contains a description of the experimental design used to obtain the data for empirical analysis in this research. A set of prediction markets was run to collect private information of traders along with market prices. The market and trading mechanism is described in chapter 4.2 in detail. Chapter 4.3 contains a description of the methodologies used to measure the constructs and variables that form the conceptual model.

4.2 Experimental Design

4.2.1 Market description

An online trading platform with a set of continuous double auction prediction markets, called SoccerExchange[7], was set up and run for the purpose of this research in order to collect data about prediction accuracy of individual traders and markets as whole. Soccer matches of the FIFA world cup 2006 were chosen as events to be predicted. A total of 128 different shares and markets were offered for trading, one share for each match and participating team.

The reason why the soccer world cup has been chosen is that most participants are well informed about this event due to the popular nature of the soccer in Europe. Participants have easy access to information about soccer matches and all relevant information will be provided sufficiently by media. In addition, it has been shown in previous prediction markets that markets about sports outcomes attract more interest and a higher number of participants (Servan-Schreiber et al. 2004). Furthermore, a high number of participants will have clear preferences for particular teams they bet on so that indicators of assimilation contrast biases can be measured easily.

4.2.2 Market design

A market design comparable to that of other prediction markets discussed in literature like the Iowa Electronic Market, Tradesports or NewsFutures was chosen.
The market included “winner-takes-all”-contracts that paid out previously defined dividends for the contract of the winning soccer team after each soccer match. To ensure participation, prizes were offered for best-performing traders. In contrast to common experimental prediction markets, participants were required to state explicitly their probability estimation (also referred to as individual forecast) for the related outcome, their source of information for judging that

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[7] See http://www.soccerexchange.org for further information

probability and their preference for an outcome when submitting a bid or ask order in the trading system. One major difference in comparison to IEM and Tradesports was the use of play money instead of real money. The use of an open source software package for building the trading platform lead to further differences in contract design and market information available to traders due to technical limitations as will be described in the following paragraphs.

The markets opened on May 28th (two weeks before the kick-off match) and remained open until July 9th (the day of the final match). Every market was open permanently for trade 24h per day until closure. The number of days a market was opened prior to the match varied from 3 days to 19 days depending on whether it was a match of the pre- or second round (for a detailed list of all markets see Appendix). Markets of the 2nd round were opened after the winning teams of the pre-round had become known so that they were opened only for a limited number of trading days prior to the match. The market was a zero-sum market, meaning that the sum of (play-money) investments by all traders corresponded to the sum of returns. To ensure participation, prizes were offered for the three participants with the highest trading profit.

4.2.3 Trading Accounts

Marketers could register for one account per person for free throughout the world cup tournament. After registration each participant received a trading account with 100.000$ of a virtual currency (SoccerDollar) which he could use to buy or sell shares or portfolios. He could use this play money to either purchase or sell unit portfolios that contain a pair of shares of both competing teams respectively. Alternatively, marketers could buy or sell shares in their respective market by trading with other market participants.

Each trader got information about his account value (with his assets valued at current market prices), current trading performance (profits/losses), a graph of trading performance history, the amount of free cash available for submitting new orders, a list of current holdings, outstanding orders and transactions history.
The system allowed the trader to see list of all tradable shares with last trading price and current outstanding bid and ask price. It permitted also to see a list of portfolios containing a pair of opposite shares for each match.

4.2.4 Contract Design

A different contract was offered for every match and participating soccer team (in total 128 different contracts for 64 matches). Contracts were tied to a final payoff of either 100 or 0 S$ depending on the outcome of a corresponding soccer match. For instance, marketers could trade either Costa Rica or Germany shares prior to the opening match. A contract was denoted usually in the form “Costa Rica vs. Germany”, meaning that the share’s assumed outcome was that CostaRica would beat Germany. After termination of the match, the holder of the winners’ share received usually 100 S$ cash payment, while the holder of the losers' share received no payment.

Every share could be traded with other traders in its respective market. There was no Initial Public Offering or initial endowment of trader accounts with shares. Instead, in order to circulate shares, traders could buy portfolios (see next paragraph) and unbundle them to sell the shares in their respective markets independently. This contract design was used in the IEM as well. Traders were not allowed to sell short but portfolios allowed them to exert similar trading strategies. Another advantage of offering portfolios is to prevent contract prizes from getting out of hand in bubbles resulting from extreme supply imbalances.

A market was usually closed on a so-called arbitration date when the outcome of the respective share (e.g. Team A has beaten Team B) was determined. The arbitration date was usually 2-3 hours after end of the match so that additional play times could be considered as well. A final payoff of 100 S$ was then paid to the holder if the respective soccer team won. Otherwise the holder received no payoff or, in the case of a draw or undeterminable result, he received 50 S$. Such a valuation function allows a transformation of the traders' probability estimations about the likelihood of an outcome into prices, given that traders are risk-neutral.

There are a number of alternative contract designs used by other prediction markets that need to be considered when comparing market results of different markets. For instance, Tradesports offered for each world cup match an additional contract for draw outcomes. Newsfutures usually tied opposite share prices together through a mechanism so that the prices of opposite shares usually sum up to 100. Share prices of opposite contracts were not tied together in the experiments of this research. In consequence, such share prices could add up to more or less than 100 depending on market liquidity and efficiency and may not have reflected probabilities accordingly. In order to adjust for such effects in analysis, also normalized prizes were considered. In addition, Tradesports limited the outcome of match results to the state after a play time of 90 min, while the contracts in this research were tied to the state of winning after termination of the game (which could be well after 90 min due to prolongation). For this reason, markets of 2nd round matches could not be compared among SoccerExchange and TradeSports as the matches often included a significant amount of additional play time that changed the base of valuation.

4.2.5 Trading rules

Traders could submit orders by selecting the appropriate share, entering the quantity of units and the maximum buying price (bid) or the minimum selling price (ask). The order was then processed as follows:

If the bid (or ask) price was above (or below) the best current outstanding ask (or bid) price in the order queue a transaction was executed at the price of the current outstanding ask (or bid) price. For instance, if another trader had previously submitted a sell order at 60 S$ that remained in the queue and if a different trader had submitted a new buy order at 70 S$ a transaction would have been executed at 60 S$. If the quantity of both involved orders differed the transaction was executed at the minor quantity of both orders. A separate order at the remaining quantity was then kept in the order queue in such a case. For instance, if one trader in the previous example had ordered to buy 50 shares while the best outstanding sell order was at a quantity of 40 shares the remaining buy order at a price of 70 S$ and a quantity of 10 shares would have been added to the queue.

The order processing mechanism checked only the best outstanding order but ignored the following orders in the queue. This means that, in the case of our previous example, if a further order at a price below 70 S$ had existed previously in the queue it would not have been executed immediately. This inconvenience was due to the software design of the open source software used. In the original market design of IEM, as described by Forsythe (1992), remaining order quantities were cancelled immediately following the transaction and not kept in the queue. However, traders could delete their unmatched orders themselves manually. Traders could not sell shares to or buy shares from themselves.

No charges and transaction fees were imposed to traders. Traders could not trade on margin; they were usually required to have a sufficient amount of free cash to submit a buy order. Traders were usually allowed to trade during the period of match beginning until arbitration date. The advantage of such a rule is to allow traders to liquidate their held contracts when the final state is more or less obvious some time before arbitration (e.g. a far ledge of one team during a match before half time).

4.2.6 Portfolios

Portfolios were offered to enable traders to buy or sell shares independently from the demand and supply situation in market. One unit of a portfolio usually consisted of a pair of shares of the two competing teams. The buyer could sell the included shares independently through the respective markets at the market price if desired. Traders could buy an unlimited number of portfolio units for every soccer match could be bought any time for a fixed price of 100 S$, given that a trader had sufficient amount of cash available in his account. Traders could also sell portfolios back to the market at a price of 100 S$ any time, given that they had enough pairs of opposing shares in their account (the portfolio price corresponded to the guaranteed final payoff of both included shares in sum).

The advantage of offering portfolios is that traders have more options of profiting from arbitrage and trading. For instance, if a trader wants to purchase a specific share and liquidity in the respective market is not sufficient he can purchase a portfolio and sell the opposite share in its respective market. Demand and supply can be better balanced and market inefficiencies like non-competitive prices and bubbles can be limited.

4.2.7 Market Information

Trading was anonymous, meaning that traders could not recognize the identity of other bidders. Traders could see the entire queue of outstanding bid and ask orders. They were provided information about past transaction prices and the volume of shares held. In addition, a continuously updated market ticker that informed through an acoustic signal about new orders and transactions was offered. The purpose of the acoustic market ticker was to increase market liquidity by making traders more vigilant which is important to prevent cheating attempts (see chapter 5 for a further discussion of cheating attempts).
Each transaction and order was logged in the logfiles.

4.2.8 Questionnaire

The experimental design included a questionnaire that was provided together with the order submission form. People were asked to state their preference for their team, a likelihood estimation of that outcome and the source of their information (see the appendix for the questionnaire in detail). This data was imposed with every order submitted. However, a trader were neither forced to fill out the questionnaire, nor was the likelihood estimation embedded in a scoring rule function as would be necessary to reveal true estimates. The reason for this was to limit complexity of the game to ensure a sufficient level of participation.

4.2.9 Security Issues

In order to prevent users from opening multiple accounts, IP addresses of each user were tracked and logged for every transaction. New account registrations needed to be approved first by the administrator before account opening. In addition, freemail addresses were not allowed. This security measure was introduced two weeks after market opening when several individuals attempted to open multiple accounts through the same ip address and computer.

4.3 Data Selection & Measurement of Constructs

In the following chapter, the methodology for measurement of the variables and constructs that were described in chapter 3.2 and 3.3 is described.

4.3.1 Data Selection

The data used for empirical analysis in this research stems from the set of experimental prediction markets that are described in 4.2. The dataset contains transactions, orders and answered questionnaires by market participants.
As mentioned in the market description (4.2.2), traders were allowed to make transactions and submit orders after beginning of the soccer matches. However, the data relevant for investigation of information aggregation and prediction accuracy includes all transactions and orders prior to the to-be-predicted event. We are only interested in the predictive capability of traders and markets. Therefore, we will consider only the data prior to beginning of the matches for analysis.

A considerable amount of data used for analysis stems from the questionnaires that were asked to fill out along which every order. However, as traders were not required to fill out the questionnaire, the responding rate was low but varied depending on the market. For purposes of data analysis of supply, demand and equilibrium price only markets that showed respondent rates above 75% and generated more than 10 orders were selected for analysis. Analogously, the data for comparing individual statistics of traders were chosen. Questionnaire responses were checked for coherence and only valid datasets were used for analysis.

4.3.2 Measurement of Market Prices

Typically, the last trading price is used in prediction markets as prediction metric as this price should reflect the most recently updated information about the to-be-predicted event. However, momentum prices can sometimes diverge from rational levels and be the results of market bubbles, non-rationally behaving traders or collaboration. Therefore, we will also measure mean trading prices. However, if we assume that the last trading price contains the most actual information by traders, it should be the most accurate prediction metric compared to mean trading prices.

In addition, we will distinguish between normalized and non-normalized market prices. As the prices of shares corresponding to opposite teams of a match are not tied to each other in this experiment they doesn’t necessarily sum up to 100 S$ although they should if the markets were completely efficient. In consequence, we can artificially normalize these prices and consider them as ratios in addition to non-normalized prices.

4.3.3 Measurement of Prediction Accuracy

The terms prediction or information accuracy and information aggregation efficiency are used simultaneous in this thesis. They describe the ability of a market or individual to make the best prediction of an event given the information about that event available. It makes only sense the measure prediction accuracy of markets in relative terms. This makes it difficult to compare the prediction accuracy of different markets which attempt to predict different events. Only the prediction accuracy of different markets run on the same event but with different settings can be compared. Analogously, it makes only sense to compare the prediction accuracy of individuals within a market but not between different markets. In order determine the prediction accuracy of a metric within a market we can compare the accuracy of two or more different metrics within the market. For instance, we can compare the predictive accuracy of the last trading price compared to the mean of individual forecasts for that market.

As a quantitative measure for prediction accuracy two main metrics are commonly used in the literature: the mean absolute forecast error (MAFE) and the percentage of accurately predicted outcomes.

The MAFE measures the absolute difference between observed and predicted outcome. In the case of binary winner-takes-all contract, it is MAFE= |o - pl| o=100 or 0=0 depending on the state of the ooutcome where pl is the last trading price.

The percentage of accurately predicted outcomes measures the percentage of cases in which the last trading price indicated an outcome (in the case of our analysis pl>50 for a and) and that prediction was later confirmed.

4.3.4 Measurement of Marginal Traders

In order to identify marginal traders, Forsythe et al. distinguished between limit orders that are entered into the order queue without resulting in an immediate trade and market orders that lead to an immediate transaction by matching a previously submitted outstanding order. Marginal traders are assumed to submit more limit orders close to the market price while non-marginal traders are assumed to submit limit orders far away from market price or at the market price. Forsythe et al. composed an index that took the value 1 if:
a trader submitted either an order that was not matched immediately but later on during a day by another order
or a trader submitted an order that was within two cents (~1%) of the last trade.

A trader was then identified as marginal trader if his index was 1 for at least three days. However, such a measure is inconvenient as it an absolute value that doesn’t take into consideration proportionally traders that joined the market later. Due to reasons of feasibility of dataset analysis only the first rule of the Forsythe's index will be used in this research. However, as price volatility in the markets of this research were much higher than in political stock market such as the IEM price variations below 1% were rarely observed within SoccerExchange and did not influence the distinction between marginal and non-marginal traders.

A further inconvenience of that measure is that it doesn't consider the ratio of marginal trades vs. non-marginal trades for each trader. Therefore, we use the relation of marginal vs. non-marginal trades as additional measure. A trader is then considered a marginal trader if more than half of his trades were marginal.

4.3.5 Measurement of Contrast-assimilation Bias

Forsythe et al conducted market polls during the Iowa presidential election market and asked traders to state their preference for a candidate and their expectation of that candidate to win (in particular after debates). In addition, they analyzed net purchases of shares of particular candidates for each trader and related them to the preference for that candidate. By this way, they inferred from a positive net purchase (purchase - sales of a particular share) of shares in conjunction with a preference for the corresponding candidate the presence of contrast-assimilation biases. Analogously to the index of days with marginal trading activity, Forsythe et al. measured the number of days with net purchase activity. They inferred from the amount of net purchases that supporters showed a higher valuation of the underlying share by buying significantly more of it (Forsythe 1992). However, this inference is somewhat ambiguous as it cannot be inferred from the quantity of shares purchased or sold how the traders valued them.

Following this methodology, we measure the percentage of trades for which the trader indicated a preference and showed positive net purchases for each trader group (marginal vs. non-marginal trader). However, due to the inconvenience of measuring just the number of days with a particular trading method, we will measure the percentage of trades with a particular trading method instead.

4.3.6 Measurement of Information Source

Forsythe et al. attempted to measure the influence of news on trading behaviour. They assumed that the occurrence of news in a market could be measured when the absolute value of change in price of a stock was greater than two standard deviations. In addition, they interviewed reporters on their assessment of news events and compared these days with trading behaviour of marginal and non-marginal traders. From such behaviour patterns, Forsythe et al. inferred that marginal traders must more often use news as source of information. (Forsythe 1992)

In this research, the source of information used by traders for building probability estimation is measured directly through a questionnaire. Traders are asked for their most important source of information (news, past performance, intuition, expert recommendation, market information or other). This data serves to compare sources of information among marginal and non-marginal traders.

4.3.7 Measurement of Competitive Price Level

Vernon Smith described a method to measure convergence towards a competitive price level (Smith 1964). The competitive price level is defined as the point of intersection of demand and supply curve in markets where no additional surplus can be extracted by trading. He uses the coefficient of convergence alpha to measure the exchange price variation relative to competitive price levels:

$$\alpha = 100 \cdot \frac{\sigma_0}{p_0}$$

where he uses the ratio of standard deviation around the equilibrium price and the equilibrium price.
We will use this indicator analogously to measure the level of competitiveness of market prices. The following paragraph will describe how to construct demand and supply curves necessary for determination of the competitive price level.

4.3.8 Constructing Demand and Aupply Curves for Prediction markets

In classic experimental economics, supply and demand curves are drawn according to reservation prices and quantities that are communicated to experiment participants. In prediction markets, marketers build their reservation prices individually according to probability estimations. In the experiment conducted for this research, participants were asked to state their individual probability estimations with each market order. This information, together with the quantity of orders, serves to plot demand and supply curves. However, as not all participants filled out the questionnaire conscientiously, it is not possible to plot a completely realistic image of the demand and supply. We will select only the markets with the highest response rates.

In addition, an analysis of the relationship of limit order price and reservation price will be conducted to reveal whether reservation prices can be inferred from limit order prices directly. Orders that were submitted and cancelled later throughout the course of a market have to be excluded from analysis as well.

4.3.9 Measuring Supply and Demand Imbalances

As discussed in 3.3.1 supply and demand imbalances could lead to prices that are either not competitive or don’t represent the mean of traders’ beliefs.

The best way to measure supply and demand structure in a market with a high number of participants would be to measure the slope of the curves. However, in experimental markets with a limited number of participants, such as in our experiment, supply and demand curves show rarely a continuous shape but rather a stepped shape. Therefore, as it is difficult to infer slope from asymmetrically stepped curves, we will infer demand and supply structure from the ratio of buyer and seller surplus.

5 Data Analysis & Empirical Results

5.1 Introduction

The following chapter presents an empirical data analysis to test the hypotheses regarding the influence of trader characteristics, allocative efficiency and demand and supply structure on information aggregation efficiency as they were elaborated in chapter 3. This analysis is conducted according to the methodology described in chapter 4 by using data obtained from a set of experimental prediction markets conducted within the scope of this research. In chapter 5.2, more general observations and impressions of the experiment results are presented. In chapter 5.3, results of the analysis of the trader characteristics such as trader type, preferences and information sources and their influence of prediction accuracy are presented. In chapter 5.4, results of the analysis relating allocative efficiency such as competitive price levels as well as supply and demand structure are presented. The chapter concludes with a reflection about the results in 5.6 and implications for practice in 5.7.

5.2 General Observations

5.2.1 Market Activity

Table 5.1 shows the statistics of the market activity. Of 132 market experiments conducted, 4 did not result in any transactions and market price. With an average of 6.4 traders per market, the number of market participants was far lower than that of comparable prediction markets. Some markets attracted only as few as 2 active traders, the most active markets attracting as much as 16 active traders. There were 38 active traders registered in total. Participants included mainly members of Erasmus University Rotterdam and other universities but also some participants from outside university. The market activity was higher for markets of popular soccer teams (as e.g. Germany, Brazil and the Netherlands). While the number of traders was low, the volume of traded contracts and the turnover was quite fair as some traders showed high trading activity.

A particular problem was the low questionnaire response rate. On average, individuals did fill out the questionnaire for 68 % of the orders submitted. However, in some markets the response rate was below 40%. Therefore, for some analysis problems requiring a high overall response rate such as the analysis of allocative efficiency and demand and supply structure only markets with at least 75% response rate were chosen. However, the low number of traders should not affect the representativeness of this research as many real world applications of prediction markets such as business forecasting markets will include only a low number of traders comparable to the one observed in the SoccerExchange experimental markets of this research. Experimental markets conducted within the scope of other research included often markets with low number of traders (see e.g. van Bruggen et al. 2006) but did not fail to draw representative conclusions.

Table 5.1: Market Activity of the SoccerExchange Experimental Markets

	Mean [Range]	Cumulated
Trading days per market	17.6 [4 - 29]	2,251
Transactions per market[8]	6.2 [1 - 59]	2,004
Orders per market[9]	18.7 [4 - 88]	2,391
Turnover (S$)	93,193.6 [8,500 - 600,360]	11,928,787
Trading volume (number of shares)	497.5 [1 - 5,008]	61,686
Active traders per market[10]	6.4 [2 - 16]	38

[8] excluding portfolio transactions from and to the market

[9] including orders that may have been cancelled later

[10] active traders are traders submitting at least 1 order

5.2.2 Prediction Performance

Overall, the markets performed quite well in predicting the favourites of soccer world cup matches. Non-normalized market prices predicted the winning team[11] correctly in 72.3% of the cases as shown in table 5.2. Normalized prices were less accurate in predicting winners with a success rate of 66.1%. However, this difference is not statistically significant. Servan-Schreiber et al. (2004) reported a success rate of 66% in predicting the favourite for comparable sports prediction markets of NFL Football matches that attracted around 50-200 traders per market. Thus, the non-normalized market prices of this research experiment performed remarkably well as prediction metric despite the low number of participants present in the market. Like van Bruggen et al. (2006) no significant correlation between trading activity and forecasting accuracy was found.

Interestingly, market prices performed better in predicting the losing teams than the winning teams, the highest lead margins occurring with non-normalized mean individual forecasts and non-normalized last transaction prices. However, the difference was not significant. This paradox should deserve attention in further research and should be analyzed in markets whose opposite binary contracts are not tied together (as in the markets of this research) and which generate a higher number of observations. This phenomenon might be explained by the tendency of traders to overestimate the winning chances of favourites and to underestimate the losing chances of underdogs as observed by Berg & Rietz (2002). This type of bias may be higher for favourites than for underdogs. Unfortunately, such a bias could not be found in the markets of TradeSports which are compared in the next chapter. The phenomenon might be related to the particular trading mechanism utilized in the SoccerExchange experimental markets[12].

Overall, non-normalized last trading prices seem to have been better prediction metrics for underdogs and winners in total than normalized last trading prices, non-normalized and normalized mean individual forecasts. But these differences are again not statistically significant.

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[11] "favorites" were implied by a last trading price P_L>50 S$, underdogs were implied by a last trading price P_L<50 S$. Matches resulting in a draw were considered as inaccurately predicted underdogs/losers

[12] for a detailed description see chapter 4

Table 5.2: Prediction Accuracy of the SoccerExchange Experimental Prediction Markets

	P_L	P_L^N	F	F^N	*p* value
MAFE	28.9	28.3	31.8	31.48	.394[13]
% of accurately predicted winners	68.2% (N=74)	68.3% (N=63)	61.6% (N=73)	67.2% (N=61)	.837[14]
% of accurately predicted losers	75.5% (N=49)	71.4% (N=63)	70.6% (N=51)	66.7% (N=63)	.788
P value (losers vs. winners)	.163[15]	.699	.305	.949	
% of accurate predictions in total	72.3% (N=123)	66.1% (N=126)	65.3% (N=124)	66.9% (N=124)	.889

Fig. 5.1 categorizes the last trading prices (non-normalized) prior to matches according to intervals of their values and plots them against the observed frequencies of victory. The correlation coefficient of both variables indicates a significant correlation with R=93,6. As can be seen from the graph, the market prices tend to systematically overestimate the probabilities for which lower real frequencies are observed in reality.

[13] one-way ANOVA

[14] Kruskal-Wallis test

[15] Wilcoxon-Mann-Whitney test

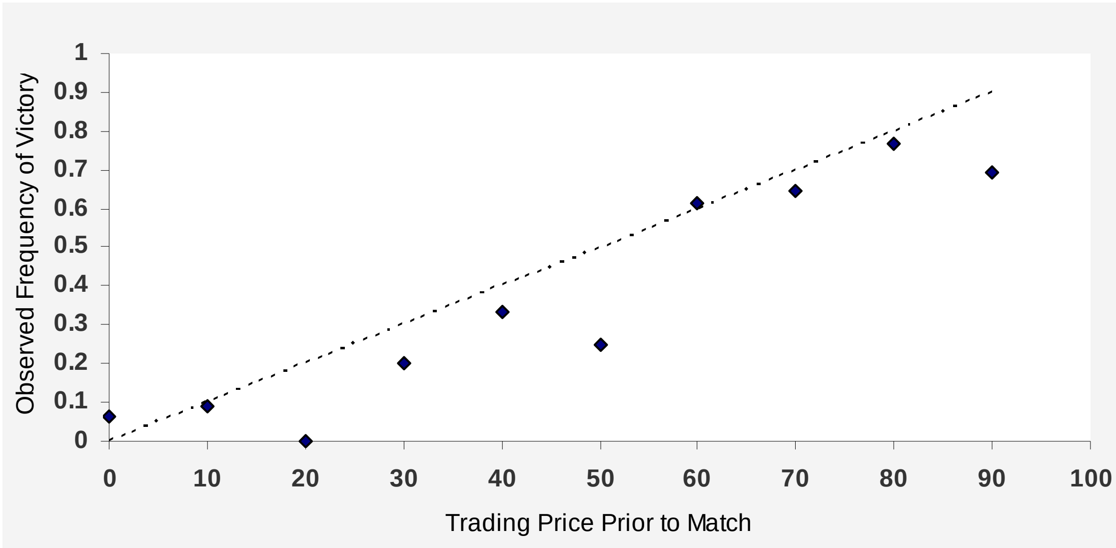

Figure 5.1: Frequency of Last Trading Prices vs. Frequency of Observed Prices in the SoccerExchange Experimental Markets

5.2.3 Comparison with Other Prediction Markets

The results from SoccerExchange were compared with data obtained from TradeSports which run similar prediction markets of the same soccer matches. Data from 45 markets, most of them of the pre-round, are available for comparison. Markets at TradeSports differed from SoccerExchange in that a third separate contract for draws was offered for each match. In addition, the trading mechanism used at TradeSports differed from the one used at SoccerExchange. Traders at TradeSports could e.g. sell contracts even without holding any of them. In that case, an amount of cash equal to the maximum possible loss of that share, taking into account the selling price, is frozen until the arbitration date and written off from the traders account in case of a loss. This trading mechanism has the same function as portfolios in providing liquidity while avoiding the necessity of an IPO.

Table 5.3 compares the two prediction markets in terms of prediction accuracy and market statistics. TradeSports counted on average about 25 times more transactions per market than SoccerExchange. The number of shares traded per market was about 8 times higher in Tradesports than in SoccerExchange. The number of traders present in TradeSports markets is not known. The mean average forecast error of non-normalized prices was 7.1 points lower for TradeSports but not significant. There was no statistically significant difference in the prediction accuracy of favourite and underdog prediction between both markets despite the huge differences in terms of market liquidity and number of transactions. These results indicate that valid predictions can also be obtained with thin populated prediction markets.

Table 5.3: Comparison SoccerEchange vs. TradeSports

	SoccerExchange	TradeSports	*p* value
Mean transactions per market	7.4[16]	182	
Mean amount of traded shares per market	497.5	2,452	
MAFE (non-normalized prices)	29.1 (N=45)	22 (N=45)	.137[17]
% of favorites (P_L>50S$) that actually won	65.4% (N=26)	65.0% (N=20)	.917[18]
% of underdogs (P_L≤50S$) that actually lose	68.4% (N=19)	62.5% (N=24)	.689[c]
% of accurate predictions in total	66.7% (N=45)	63.6% (N=44)	.708[c]

[16] excluding portfolio transactions

[17] Wilcoxon Mann-Whitney test

5.2.4 Cheating Attempts

In the first two weeks of market operation, individuals could register without verification of their accounts. At least 5 different individuals tried to open multiple accounts from the same ip-address and computer although this was prohibited by the terms & conditions. After two weeks, an additional security measure was added to the existing ip-address tracking system that was already in place. The accounts of new registrants needed to be verified by the administrator prior to trading. Existing multiple accounts that were found to be opened by the same individuals were deactivated. However, it was difficult to verify whether different individuals attempted to collaborate by using one account purposefully for conducting disadvantageous trades to the benefit of another account.

Fig 5.2 shows one example of the use of multiple accounts for cheating purposes. The graph plots the price history of the contract CRC-WIN-GER, which reflects the probability of the underdog Costa Rica to beat the favourite Germany. The price suddenly climbed from 5 to 90 S$ on 02/06/2006 although no significant news about that team had occurred. One person used his accounts to first buy out all outstanding buy and sell orders in the market to the disadvantage of the one account and then to buy the shares at an irrational price from another of his accounts to the benefit of the other account. The trader was identified as cheater and excluded from the market shortly after that event.

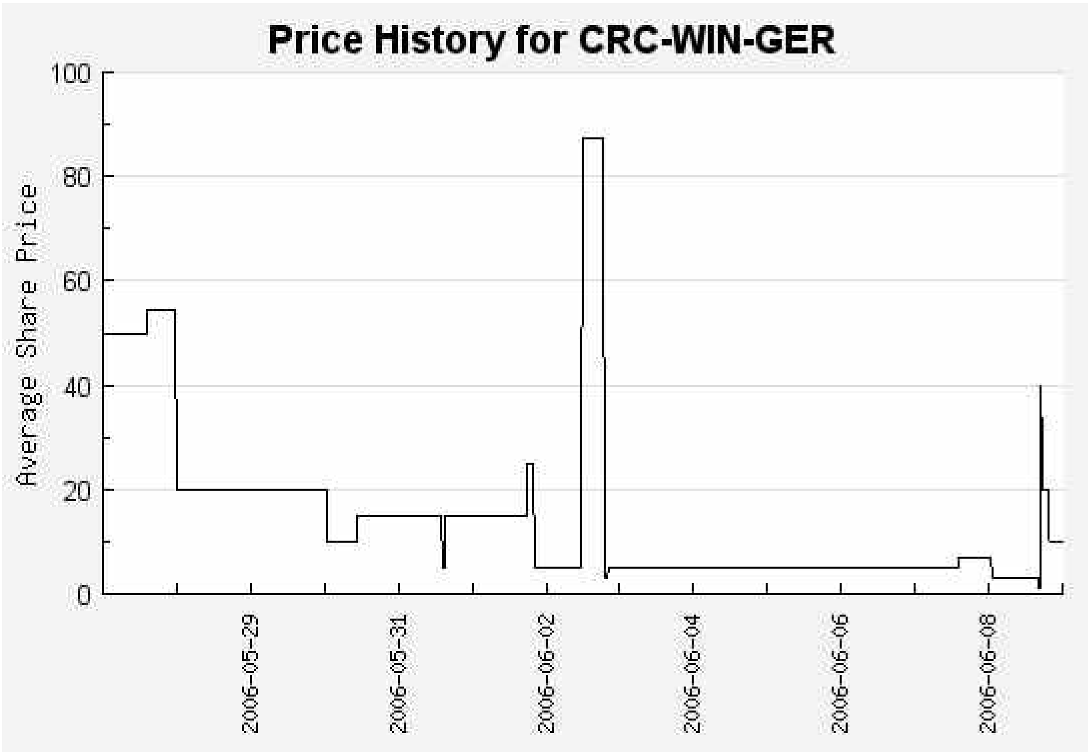

Figure 5.2: Price History Showing Malicious Trading Behavior

Fig 5.3 depicts an event that is suspected to be of similar nature. It shows the price history of the contract JPN-WIN-BRA, which reflects the probability of the underdog Japan to beat the favourite Brazil. After the price adjusted to a level around 5 S$ it climbed suddenly to 17 and 38 S$ on two occasions. Two individuals were responsible for the entire transactions that lead to the high price levels. They were often logged in the system at the same time using two different ip addresses. It can only be suspected but not confirmed that they engaged in collaboration. In theory, such incidents do only occur in market with low number of participants. If the number of participants is sufficiently high, other traders can enter the market and profit from orders at irrationally high or low prices, thus pushing the price back to a normal level. However, prediction markets have rarely enough participants who are continuously present to track the market permanently.

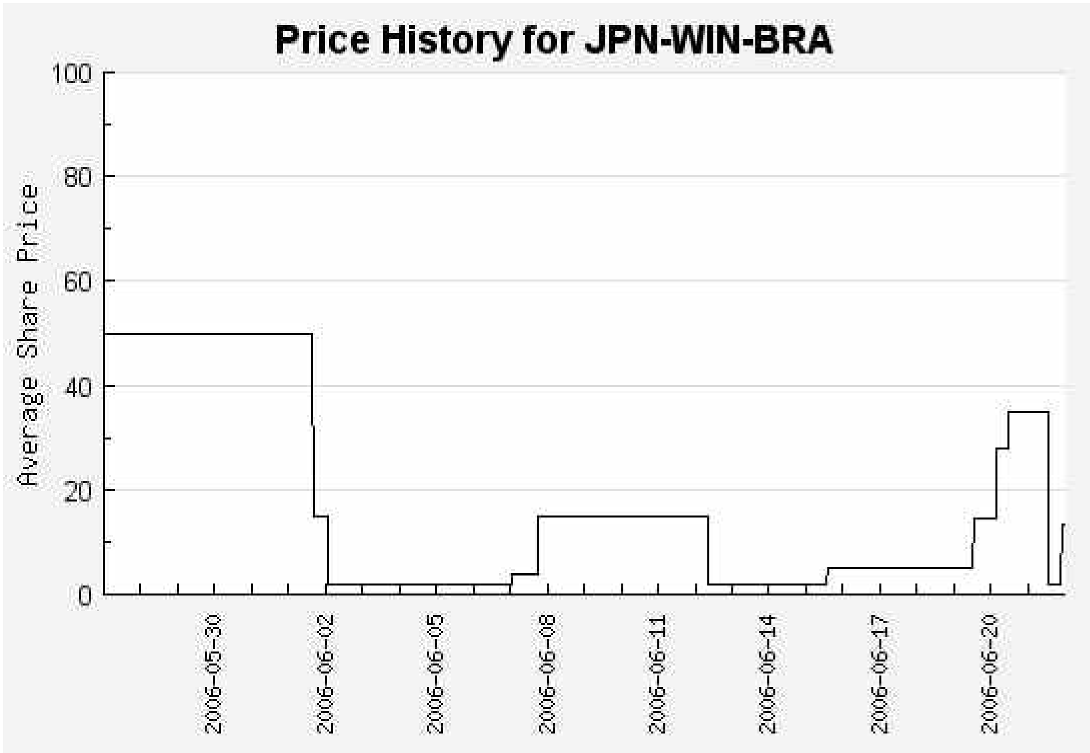

Figure 5.3: Price History of a Contract showing suspicious trading behavior

Figure 5.4: Price History Showing Anomalous Trading Behavior

Fig. 5.4 shows the price history for the share USA-WIN-GHA. On June 19th, a person registered for an account and used his entire cash to submit a buy order of 1000 shares at a price of 100 S$. Apparently, such an order is completely irrational even if this person had believed that the chance for USA to win would be 100%. Even in the case USA would win, the person could not obtain any profit from trading. Two possible explanations can be provided for such a strange behaviour. Either the trader did not understand the game, he made a mistake when filling out the order form or he intended to collaborate with another person who could benefit from selling USA shares for a “risk-free” maximum price. The author of this research intervened in this situation by selling 1000 USA shares at the offered bid price to the mentioned person.

These examples clarify the problems that are associated with the use of play-money markets. If play money is used individuals may not have the incentive to behave rationally in the sense that each account is used in the purpose of earning profits. Prices then don’t reflect the true probability judgements of each individual. In the last section of this chapter, some strategies are discussed to avoid such problems when conducting prediction market experiments.

All cheaters were excluded from the first part of the analysis regarding the first part of the conceptual model. In addition all markets for which cheating attempts were observed were excluded for the analysis regarding the second part of the conceptual model.

5.2.5 Individual Predictions and Market Prices

Fig 5.5 depicts the relationship between the mean probability estimation by individual traders and the last trading price for each market. As can be seen on the graph, the relationship is significant (R=0.883, p=.000).

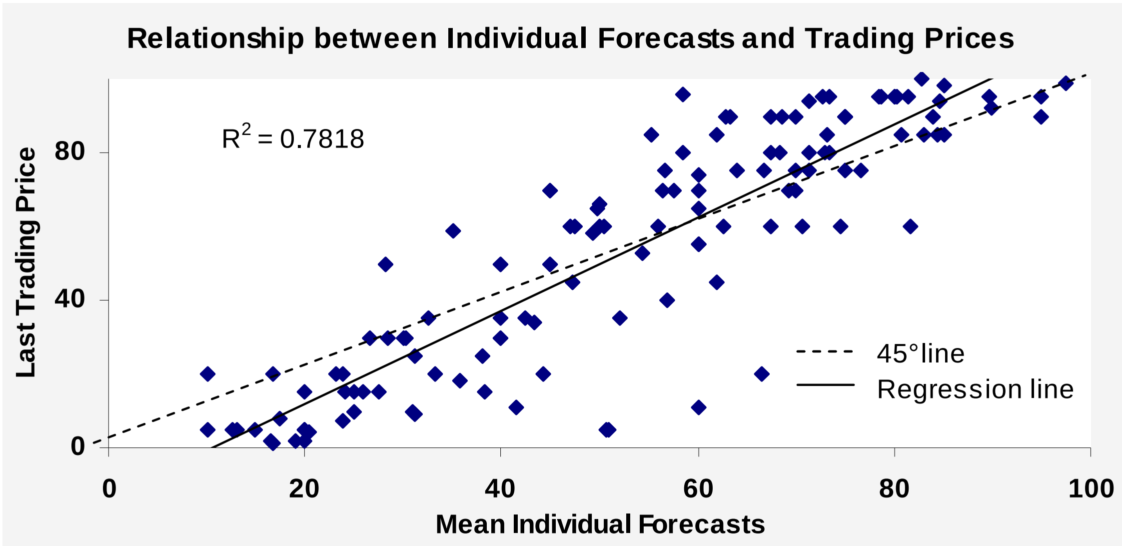
Relationship between Individual Forecasts and Trading Prices
R^2 = 0.7818
45°line
Regression line
Last Trading Price
0
40
80
0
20
40
60
80
100
Mean Individual Forecasts

Figure 5.5

5.3 Trader-based Model of Information Aggregation

5.3.1 H1: Presence of Biases

As discussed in chapter 2, Foresythe et al. (1992) claimed that individual preferences would affect objective judgments of traders. While Forsythe et al. did not measure directly the link between individual preferences and forecast accuracy but only between individual preferences and trading behaviour (net purchases) we measure the link between individual preferences and individual forecast accuracy. The results are shown in table 5.4.

Table 5.4: Trader Type and Preferences

	Marginal Traders	Non-marginal Traders	*p* value
Avg. percentage of traders indicating a preference for either team A or B when submitting an order	78.5%	77.2%	0.926[19]

There are no significant differences in indication of a preference between marginal and non-marginal traders. Therefore, H1 can be confirmed.

H1: Marginal traders don't show a higher presence of contrast-assimilation biases than non-marginal traders

As mentioned in chapter 2, one hypothesis by Forsythe et al. (1992) was that preferences for an assets' underlying outcome would lead to judgment biases and less accurate predictions in individuals. Table 5.5 shows an comparison of mean individual forecast errors for the same prediction markets on SoccerExchange grouped by the level of preference as indicated by individuals. Individuals were asked to state their preference for a soccer team.

Table 5.5: Presence of Biases and Forecast Accuracy

	Preference for the underlying outcome	No preference	Preference for the opposite outcome	*p-value*
MAFE	34.1 (N=39)	31.6 (N=39)	36.7 (N=39)	.685

As can be seen, the forecast error was slightly lower for individuals who indicated that

[19] t-test

they had no preference for either of the related outcomes while the MAFE for individuals indicating a preference for the opposite outcome are slightly larger. However, these marginal differences are not significant.
In other words, no evidence was found for the claim that the occurrence of certain preferences for a certain outcome indicates a systematic judgment bias in individuals.

5.3.2 H2: Trader Type and Source of Information

Table 5.6 presents the percentage of trades for which a particular source of information was selected by marginal and non-marginal traders. As can be seen from the table, most traders used news as source of information for making individual predictions, followed by intuition and past performance of soccer teams. Differences in the choice of source of information are not significantly different for both groups except for expert recommendation. Marginal traders use this source of information in 16% while non-marginal traders use it almost never. No statistically significant difference could be found for the percentage of traders indicating a preference for any team neither. H2 can therefore be confirmed:

H2: Marginal and non-marginal traders don't differ in their choice of information sources

Table 5.6: Trader Type and Source of Information

(% of trades for which traders used the following information source)	**Marginal traders**	**Non-marginal traders**	***p* value**[20]
News	33.6%	34.4%	.850
Past Performance	19.6%	17.6%	.320
Intuition	22.0%	31.6%	.287
Expert recommendation	16.3%	0.5%	.076[21]
Market Signals	7.4%	13.9%	.884
Other	1.0%	2.0%	.623

[20] t-test for continuous variables

[21] significant at the 0.10-level

5.3.3 H3: Trader Type and Individual Information Accuracy

Table 5.7 shows the statistics for the two groups of marginal and non-marginal traders. All active traders who where found to cheat as well as the author who participated in the game were excluded from this analysis. Both groups are distinguished according to the first rule (number of days with marginal trading activity) as defined by Forsythe et al. (1992) Marginal traders represent only about one third of the trader population. They participate in a higher number of trades and submit a higher number of orders, thus confirming the observations made by Forsythe et al. (1992) However, the results of this research differ regarding the median trading profit, which was negative for marginal traders and positive for non-marginal traders. H3 can therefore be confirmed:

H3: Marginal and non-marginal trader don't differ in terms of individual information accuracy

Table 5.7: Comparison Marginal vs. Non-marginal Traders

	Marginal traders	**Non-marginal traders**	***p* value** [22]
Number of traders	13	25	
Mean number of transactions (excluding portfolio transactions)	76.9	12.9	.000
Mean number of orders	169.2	13.6	.000
Median trading profit (from trading prior to match)	-7275	235.5	
MAFE	36.7	43.4	.693

As can be seen from the table 5.7, marginal traders showed a lower MAFE (6.7) but this difference was not significant.

[22] Mann-Whitney test

5.3.4 Source of Information and Information Accuracy

No major differences were found between marginal and non-marginal traders concerning the choice of information source. We can ask further whether the source of information determines information accuracy of individuals. Table 5.8 gives an overview over mean prediction accuracy (percentage of accurately predicted favourites/underdogs) of individuals depending on the choice of informational source. The values were compared for the same set of markets in order to measure the relative prediction accuracy.

Table 5.8: Sources of Information and Individual Prediction Accuracy

Source of information	Accurately predicted winners/losers
News	64.4% (N=101)
Past performance	67.4% (N=89)
Intuition	48.1% (N=156)
Expert recommendation	52.3% (N=65)
Market Information	44.4% (N=27)
Other	77.8% (N=9)
P value[23]	.010

As can be seen in the table, there are significant differences in mean individual prediction accuracy depending on the source of information. The high values for traders using “other sources” will be ignored due to the low number of observations.

Interestingly, traders using market information (e.g. price signals) made less accurate predictions than traders using other sources of information. This may imply that traders don’t improve their forecast accuracy by learning from price signals. Traders relying on intuition show less prediction accuracy than those relying on news and past performance, which represent hard fact information.

Therefore, a new hypothesis can be added to the conceptual model.

The source of information determines individual prediction accuracy

[23] One-way ANOVA

5.4 Market-based Model of Information Aggregation

5.4.1 Overview

In order to analyze the market efficiency as proposed in chapter 3.3 only 19 markets were selected according to the ratio of valid questionnaire answers. Only markets with at least 75% of orders submitted together with valid questionnaires were included in the analysis.

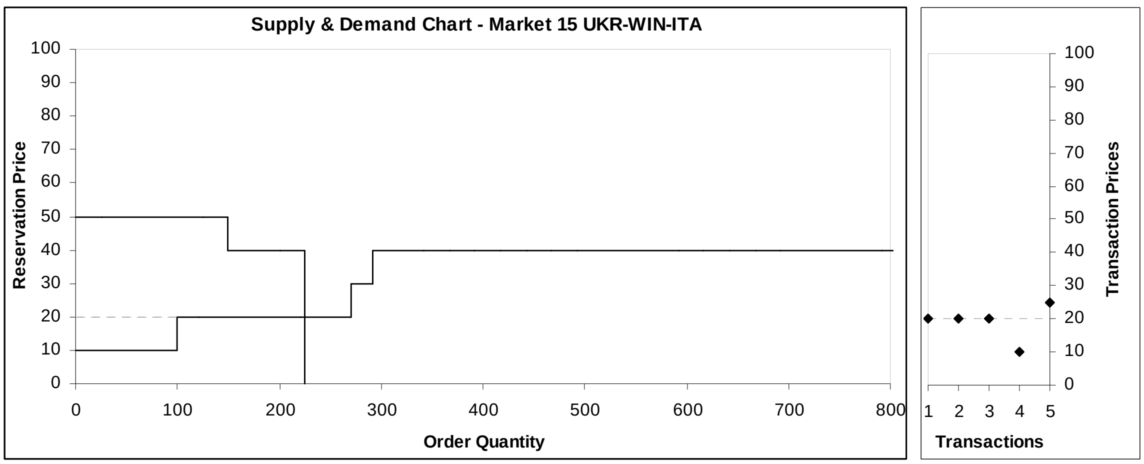

Figure 5.6: Supply/Demand Structure and Transaction Prices for an Exemplary Market

Fig. 5.6 depicts one exemplary market. Supply and demand curves, as depicted in the left part, were constructed according to the reservation prices (implied by probability estimates) and quantities that were stated by traders in the questionnaire and order form. Reservation prices should represent the outer boundary for building limit order prices if traders are assumed to behave rationally. However, in some few cases the true order prices violated the boundaries implied by reservation prices. Therefore, these demand and supply functions may not represent the real situation accurately but rather a close approximates of the demand and supply structure and equilibrium market price levels.

The right part of the graph plots the occurred transaction prices in sequence. The dotted line represents the computed equilibrium market price that occurs at the intersection of demand and supply curves.

Fig 5.8 plots the equilibrium prices against last trading prices. A quite significant relationship between equilibrium prices and last trading prices can be found (R=0.83). However, there is an even stronger relationship between mean individual forecasts and equilibrium prices (R=0.93) as shown in Fig 5.7. This seems to confirm our assumption that the market mechanism might work as an averaging mechanism.

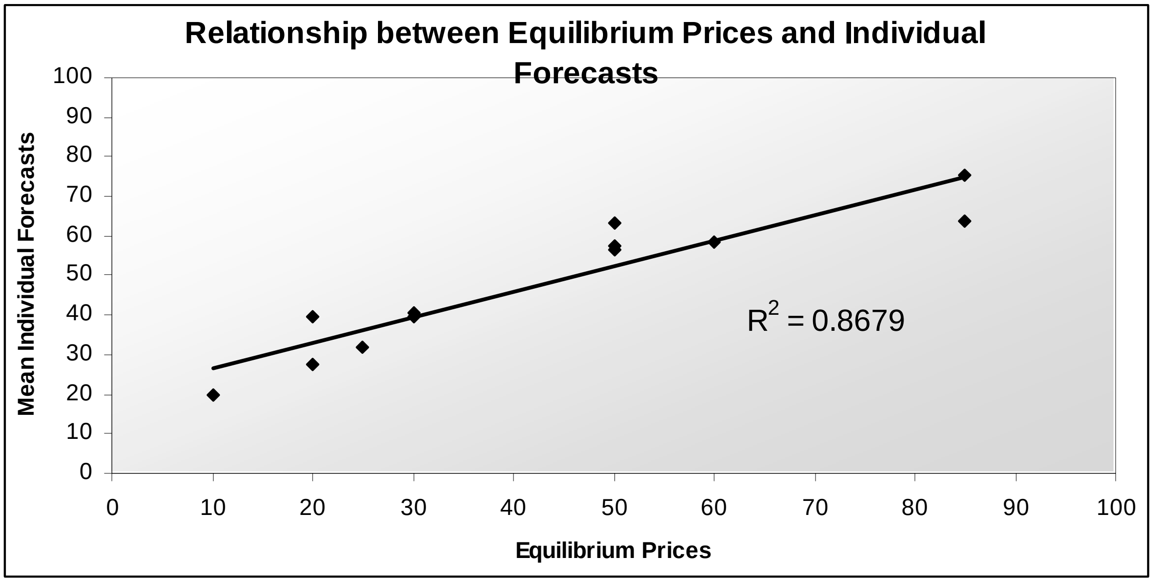

Figure 5.7

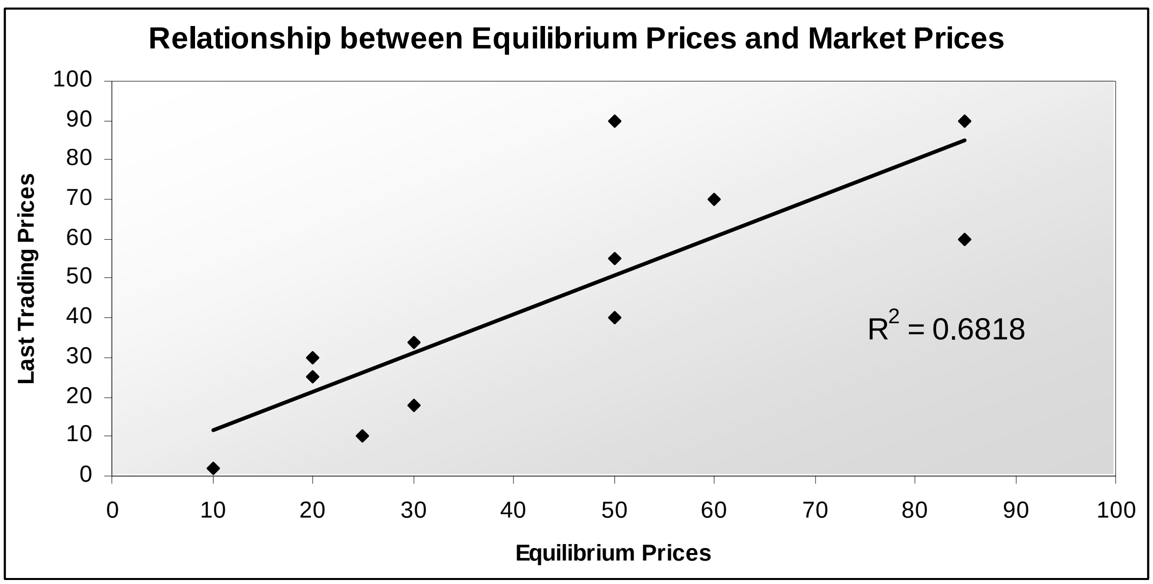

Figure 5.8

Table 5.9: Analysis of Allocative Efficiency and Supply/Demand structure for a sample of 19 markets

No	Buyer Rent	Seller Rent	BR/SR-score	P_L[24]	P_0[25]	MAE(P_L)-MAE(P_0)[26]	α	Observed outcome
1	9410	10780	0.03	94	64	-30	25.0	100
2	290	4225	0.44	15	30	-15	16.1	0
3	0	7000	0.50	95	100	-5	6.1	50
4	1000	250	0.30	2	10	8	8.0	50
5	2100	12700	0.36	90	95	5	4.4	100
6	3700	28500	0.39	10	25	-15	17.8	0
7	7800	1250	0.36	30	20	10	14.0	0
8	545	60	0.40	40	50	10	18.0	50
9	0	9425	0.50	60	85	25	13.1	100
10	50	0	0.50	90	85	-5	4.1	100
11	4500	1750	0.22	70	60	10	10.8	0
12	4250	2025	0.18	34	30	-4	4.5	100
13	12595	1000	0.43	85	50	35	19.0	0
14	6500	0	0.50	90	50	-40	40	100
15	6000	1000	0.36	25	20	5	5	0
16	8020	1000	0.39	18	30	12	14.1	100
17	113640	0	0.50	60	50	10	23.6	0
18	18000	0	0.50	59	30	29	24.9	0
19	2000	9000	0.32	55	50	-5	14.6	100

Table 5.9 gives an overview over the 19 markets that were selected for allocative efficiency analysis. The amounts and ratios of buyer and seller surplus differed among markets as did the convergence of trading prices around the equilibrium price, measured through the coefficient of convergence (α). There are no significant differences between the mean forecast error of equilibrium prices and the mean error of last trading prices (p=.695).

A pattern in the adjustment process (see selected markets in the appendix E.2) towards

[24] last trading price

[25] equilibrium price

[26] difference between mean absolute forecast error of the last trading price and mean average forecast error of the equilibrium price (referred to as relative prediction accuracy)

an equilibrium cannot be observed.

5.4.2 H4: Supply and Demand Structure

Our hypothesis stated that demand and supply structure would affect prediction accuracy. From a methodologically point, it is problematic to measure the influence of a determinant by comparing the prediction accuracy of different markets (which may be caused mainly by different levels of information about the to-predicted-outcome rather than another determinant). Therefore, we compare the mean prediction error of last transaction prices with the mean prediction error of mean individual forecasts for each market and build a score that expresses the ledge of one metric over the other. To measure the ratio of buyer and seller surplus a score that measures the proportion of buyer surplus of the total surplus minus 0.5 (|BS/(BS+SS)-0.5|) was built. The more equal buyer and seller surplus are the more symmetric supply and demand structure should be.

Table 5.10 shows a regression of the buyer/seller surplus ratio score on the prediction accuracy (implied by the differences in forecast error between last trading price and the equilibrium price). No statistically significant relationship could be found. Thus, we cannot confirm our hypothesis H4 that demand and supply structure would affect the prediction accuracy of equilibrium prices.

Table 5.10: Regression of the BR/SR-score against relative forecast accuracy

Coefficients[a]

Model		Standardized Coefficients	t	Sig.	95% Confidence Interval for B	
		Beta			Lower Bound	Upper Bound
1	(Constant)		-.960	.351	-41.829	15.675
	BR/ SR-score	.274	1.173	.257	-32.113	112.466

a. Dependent Variable: MAE equilibrium price - MAE last trading price (difference in prediction accuracy between last trading price and equilibrium price)

5.4.3 H5: Allocative Efficiency (Competitive Price Level)

Our hypothesis stated further that the allocative efficiency of markets implied by a low coefficient of convergence would affect the prediction accuracy of last trading prices. No statistically significant relationships could be found as shown by table 5.11 which provides the test statistics for the regression of the coefficient of convergence on the difference in prediction accuracy among equilibrium prices and last trading prices.Therefore, H5 can be rejected.

Table 5.11: Regression of the coeff. of convergence against rel. forecast accuracy

Coefficients[a]

Model		Standardized Coefficients	t	Sig.	95% Confidence Interval for B	
		Beta			Lower Bound	Upper Bound
1	(Constant)		1.378	.186	-5.980	28.523
	coeff. of convergence	-.302	-1.308	.208	-1.608	.377

a. Dependent Variable: MAE equilibrium price - MAE last trading price (difference in prediction accuracy between last trading price and equilibrium price)

5.5 Summary

Fig. 5.9 summarizes the results obtained so far. The conceptual model is adapted according to the empirical evidence gained. While no relationship between trader type and individual information accuracy and source of information could be observed, the source of information appeared to determine individual information aggregation. Presence of biases did not significantly affect individual information accuracy. No relationship could be found for the demand and supply structure as well as the allocative efficiency.

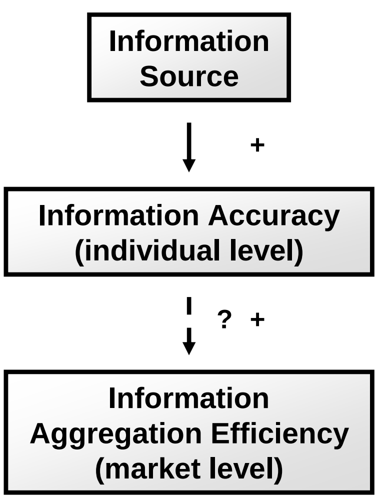

Figure 5.9: Modified Conceptual Model

The relationship between individual information accuracy and information aggregation efficiency remains unclear and deserves further research. The results obtained from this research indicate a significant relationship, especially with theoretical equilibrium prices.

5.6 Reflection on the analysis results

5.6.1 Trader-based Model of Information Aggregation: Presence of Biases

The hypothesis that the presence of biases implied by indicated preferences would not affect individual information accuracy has been confirmed. The results suggest that the role of biases has been overemphasized in past research. Whether or not a trader has a preference for the soccer team does on average not affect his prediction accuracy.

5.6.2 Trader-based Model of Information Aggregation: Information Source

No relationship between trader type and choice of information source could be found as hypothesized. However, a relationship between the source of information and mean individual forecast accuracy could be found. The results are in line with the assumption by Forsythe et al. (1992) that the ability to identify news as source of information would determine information accuracy on an individual and market level. However, whether someone possesses relevant information cannot be inferred from his trading behaviour. Kambil and van Heck (2002) posited that traders have to be knowledgeable about the issues the market seeks to address. The results of this research seem to support their claim. However, the choice for a source of information does not necessarily indicate the level of knowledge a persons has.

Under more experimental laboratory conditions the trader population could be artificially composed of traders with different levels of knowledge and asked to solve pre-determined forecasting task in order to verify whether a knowledgeable trader population is really necessary to achieve accurate forecasts and whether this can be achieved by selecting traders according to their source of information.

5.6.3 Trader-based Model of Information Aggregation: Trader Type

Why the significant role of trader type and trading behaviour was found to indicate information accuracy only in north American electoral markets analyzed by Forsythe et al. (1992) and not in European electoral markets or sports prediction markets remains unresolved. It may be a coincidence that North American traders interested in politics and thus more knowledgeable at the same time show superior trading abilities and less biases. The type of experiment conducted within this research including the collection of individual forecasts should be repeated in the light of North American electoral markets to reveal the individual forecast accuracy of marginal and non-marginal traders and to verify whether there is any directly measurable relationship.

5.6.4 Market-based Model of Information Aggregation

In the data analysis no statistically significant relationship between measures of allocative efficiency and relative prediction accuracy could be found. The hypothetical equilibrium price was not found to predict the outcomes more accurately if supply and demand curves had a more symmetric structure. Neither was it found to predict the outcomes significantly more accurately than the last transaction price. The hypothetical equilibrium prices correlated stronger with mean individual forecasts than with observed last transaction prices independent of the shape and symmetry of demand and supply curves. These results seem to confirm the theory that the mean of individual beliefs may be independent of the distribution of beliefs among traders established by Gjerstad (2004). The results also indicate that the double auction market mechanism seems at least partially to work as an averaging mechanism since equilibrium prices are closer to mean individual beliefs than to observed market prices. However, the last transaction prices observed in markets often deviate from the hypothetical equilibrium price without being significantly less accurate prediction metrics than the hypothetical equilibrium price. Thus, there may be a further aggregation mechanism that hasn't been described yet.

The results of analysis of alllocative efficiency obtained within the scope of this research need to be interpreted with care as the data regarding submitted individual forecasts was not complete. The issue of allocative efficiency in the context of prediction markets deserves further attention and more experimental investigation under more controlled laboratory settings. In particular, it should be made sure that traders elicit their true beliefs when submitting probability estimations along with orders. This can be achieved e.g. by including scoring rules for probability estimates such as described in chapter 2 and tying of that scoring rule to a reward mechanism.

5.7 Reflection on Practical Implications

The conclusion drawn from this research may have in particular implications for conduction double auction markets with limited number participants such as in business forecasting situations.

In practise, the markets should be designed such that only knowledgeable individuals using proper sources of information are attracted. Mere self selection through the market incentive mechanism seems not to be sufficient to attract only knowledgeable individuals as a high number of individuals in the SoccerExchange markets e.g. relied on intuition as source of information. A pre-selection mechanism, based upon questionnaires that test for relevant knowledge in the field of the to-be-predicted event might serve this purpose. Van Bruggen et al. (2006) provide an example of such questionnaires in their research.

Following this paradigm, it should be avoided to attract uniformed traders intentionally as proposed by Wolfers & Zitzewitz (2004).

It might be of advantage to include questionnaires for revealing traders private information in the form of probability estimations and to compare the mean beliefs with market prices. In the case that orders are submitted but transactions did not occur, these estimates can serve as an alternative prediction metric.

Much experience was gained regarding the issue of cheating behaviour while conducting the SoccerExchange experimental markets. Solutions for that problem are discussed in the next chapter.

5.7.1 Preventing Cheating

As shown by the experiment, one of the most obvious challenges for obtaining valid experimental results is to prevent marketers from engaging in cheating or manipulative behaviour. While the problem of manipulation for the purpose of influencing prices has been discussed to some extend in the literature the problem of cheating for the purpose of gaining profits from malicious inter-account trade has not been discussed sufficiently.

In markets with real-money marketers have no incentive to create multiple accounts or collaborating with other traders for cheating purposes and fraudulently inter-account trade. However, as noted by Servan-Schreiber et al. (2004) law regulations in several countries prohibit the use of real-money prediction markets for non-academic purposes.

If a prediction market attracts a sufficiently high number of active traders malicious inter-account trade could be prevented by other traders who could intervene in such situation and profit from shares offered for buying or selling at irrational prices. Servan-Schreiber et al. (2004) did not observe any significant difference between the prediction accuracy of play money and real money markets as the compared markets in their research attracted enough participants. However, if the experimenters fail to attract enough participants other precautions need to be taken in order to prevent market manipulation.

The following actions and precautions can be taken to attempt cheating:

Excluding Auspicious Traders

This type of security measure was deployed several times during the course of SocceExchange. However, it is difficult to define when cheating behaviour occurs and when not. One way to detect cheating behaviour is to track irrational behaviour. Irrational behaviour usually occurs when no profit can be obtained by a particular transaction or another trading strategy, such as including portfolio transactions, would be more profitable. The problem of excluding suspicious traders lies in the possibility of erroneously excluding non-fraudulently traders. Irrational behaviour can also be attributed to a misunderstanding of game rules or incorrectly filled out order forms.
In addition, previously performed actions of fraudulently traders at the time of detection may have affected the market price and cannot be undone.

Intervening with Supervisor Traders

Another possible solution to prevent cheating is to monitor the game permanently and to intervene if suspicious orders are placed in order to prevent suspicious traders from profiting from their cheats. One exemplary situation where a trader wanted to buy shares at a non-rational price of 100 S$ is described in 5.4.2. However, here it comes again to define suspicious orders and the problem of influencing endogenous market dynamics through external influences.

Account Approval and Identity Management

A way to prevent the creation of multiple accounts is to track ip addresses of traders and to refuse approval of multiple accounts opened from the same ip address and/or computer. However, participants may have access via networks, as e.g. university networks, that use a similar ip address. In addition, this method cannot prevent different traders from collaborating.

A further way of verifying user identity is via verification of email addresses and identities by disallowing registration with freemail addresses as it was done in the case of SoccerExchange. However, as many people use freemail addresses this precaution will prevent many individuals from participating.

Tying Rewards not Entirely to Trader Performance

In the case of SoccerExchange, rewards were tied entirely to individual trader performance. In consequence, individuals had incentives to attempt fraud by opening multiple accounts or collaboration as they could influence their performance by that way. Other prediction markets such as Stoccer[27] avoided such a direct tying between trader performance and rewards by selecting the best traders according to their performance and finally allotting winners among this high-performer group. However, such an approach can also motivate traders to create even much more multiple accounts to maximize their winning chances, anyway.

Adding Scoring Rules

A new approach would include a scoring rule mechanism, such as for the case of Soccerexchange, and tying reward to the performance of both trading profits and prediction accuracy of individual forecasts. By this way, cheaters could only profit if they would provide accurate individual forecasts and not solely by trading.

Increasing Market information

Continuously updated market tickers, SMS services and automatic agents could be used to increase reactivity of other traders in situations where cheaters attempt to clear all outstanding orders.

Limiting Trading Hours

Cheaters require lonely markets to execute their fraudulently trades. In order to make sure that a sufficiently number of traders is present in the market the trading time could be reduced (e.g. to a time frame of 15 min each day and shortly before the to-be-predicted event). Another solution could be to accept all bids during a submission phase throughout a day while adding to a bidding queue and to execute them only once every day or every hour. By this way, a clearing of outstanding orders could be avoided.

[27] http://www.stoccer.com

6 Discussion & Conclusions

The following chapter includes a discussion of the findings obtained from this research as well as a conclusion. In addition, recommendations regarding opportunities for further researches are made.

6.1 Discussion

This research attempted to identify relevant determinants of information aggregation efficiency in prediction markets. It was investigated whether a certain type of traders, called marginal traders, show higher individual information accuracy than other traders and thus account for efficient information aggregation in prediction markets as suggested by Forsythe et al. (1992). In particular, it was investigated whether this trader type achieves higher individual information accuracy by choosing sources of information differently and showing fewer biased judgments as proposed by Forsythe et al.

Data for empirical analysis was collected through a set of 128 prediction markets that were run during the FIFA soccer world cup 2006. The markets showed relatively high prediction accuracy, implied by their market prices and mean individual forecasts. Despite the low number of participants the markets achieved a level of prediction accuracy comparable to that of other prediction markets such as TradeSports.

No significant difference in prediction accuracy, source of information and presence of biases (implied by indicated preference for soccer teams) could be found between marginal and non-marginal traders. In other words, no evidence was found for the theory that marginal traders would show higher prediction accuracy on an individual level and therefore drive the high information aggregation efficiency on market level. Thus, the hypothesis that trader type would not affect information aggregation efficiency was confirmed.

However, it was found that the source of information affects forecast accuracy on an individual level and thus might influence information aggregation efficiency on an aggregate market level.

In a second step, it was investigated whether market efficiency characteristics such as competitive equilibrium price level and supply and demand structure affect prediction accuracy of markets. A new experimental method was used to measure individual forecasts, market prices and order quantities at the same in order to display supply and demand curves and to determine the equilibrium price level.

No evidence for a relationship between demand and supply structure or level of price competitiveness and prediction accuracy of market prices could be found. No difference in prediction accuracy between mean individual forecasts, equilibrium prices and last trading prices could be found. However, a strong relationship between mean individual forecasts and both equilibrium prices and last trading prices could be found.

However, the experimental results obtained through the experiments of this research should be interpreted with care. Some markets suffered from manipulation by cheaters and a low number of individual forecasts due to low questionnaire response although it was tried to isolate these effects from analysis. Further experiments and more representative data are needed to confirm the conclusions reached in this research.

6.2 Recommendations for Further Research

The findings indicate that market designers and research need to pay less attention to the composition of trader population and to trader characteristics such as the presence of biases or trading behaviour when setting up and investigating prediction markets. However, the utilized sources of information deserve further attention. As shown by this research, there might be potential for an increase in prediction accuracy if market designer manage to control this variable among traders.

The combination of individual forecasts and prediction markets offers a powerful tool for further analyzing information aggregation efficiency in prediction markets. The classical experiments with double auctions conducted by Chamberlain (1948) and Smith (1962) can be applied to predicting events as well and offer a great source of inspiration for further experiments with prediction markets.

Existing research focused on using more realistic experimental settings. A higher degree of experimental situation within laboratory settings would allow investigating isolated effects such as demand and supply shocks, price formation or trading efficiency more in detail.

One problem in researching prediction markets concerns the reproducibility and comparability of results. As the inherent predictability and aggregate uncertainty varies depending on the to-be-predicted outcome the results of different markets can not simply be compared as it is often done in literature. Only markets with the same to-be-forecasted outcome, controlled boundary conditions and quantifiable and measurable dependent and independent variables should be compared in order to be able to draw representative conclusions.

The number of possible determinants affecting forecast accuracy that have been identified by several scholars in the field has grown to an unmanageable number of disruptive factors that might affect result results. While many scholars have been attracted by the fascinating accuracy that has been achieved by those markets in real world settings further experimental research attempts should focus on isolating influences which may be achieved only by strict laboratory conditions. However, this would prevent researches in turn from obtaining practice-relevant results but is necessary to gain insight in the influence of all determinants.

The relationship of private information and aggregate market information deserves more attention by future research. Only if research achieves to determine the information aggregation mechanism market designers will be able to better control forecast accuracy and interpret results.

7 Acknowledgements

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Appendices

A Description of the Trading Platform

The following chapter gives an impression of the experimental markets run in the scope of this research.

Fig. 0.1 depicts the starting page of the online prediction markets. The entry screen showed the newest offered markets, the busiest markets in terms of trading volume and the highest scoring traders. The traders could get a list all active markets as well as markets that have been closed.

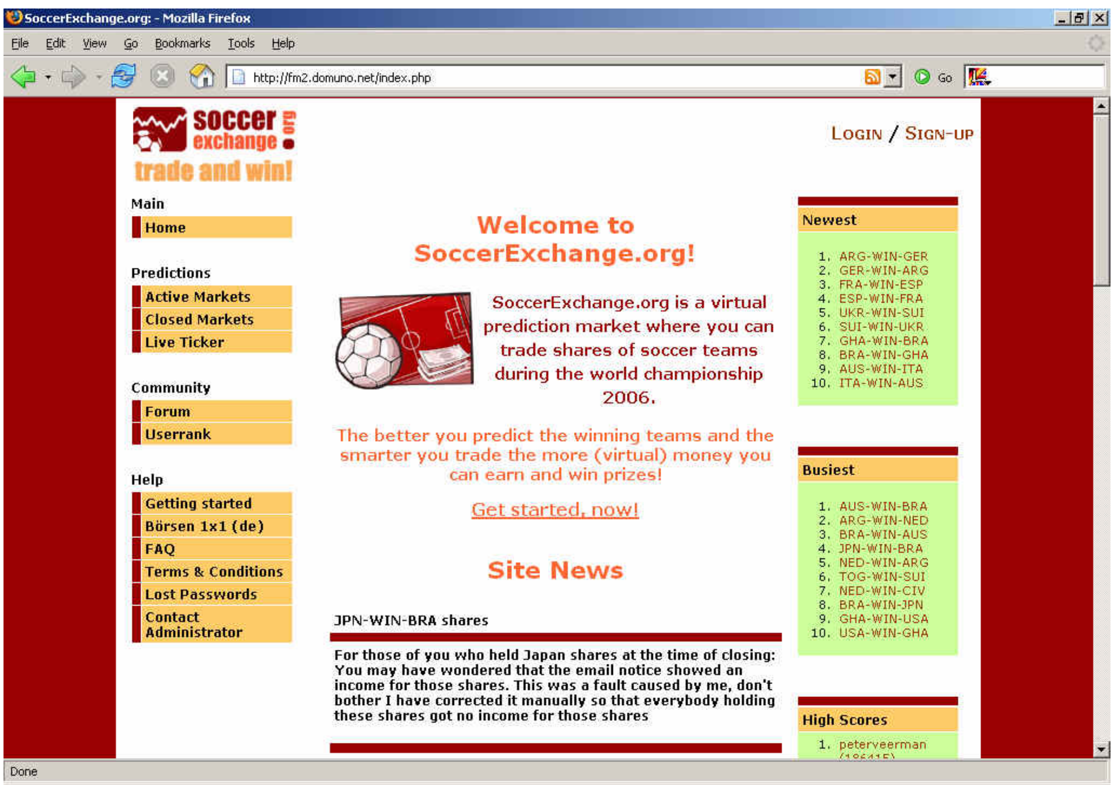


Figure 0.1: Entry Screen

Fig. 0.2 depicts the listing of active markets. The screen listed at shares in pairs of opposed soccer teams and with symbols to facilitate selection. The list provided information about last transaction prices, best outstanding bid prices and best outstanding ask prices. Traders could sort the list according to contract name, category (world cup tournament round), match date as well as ask/bid/last price.

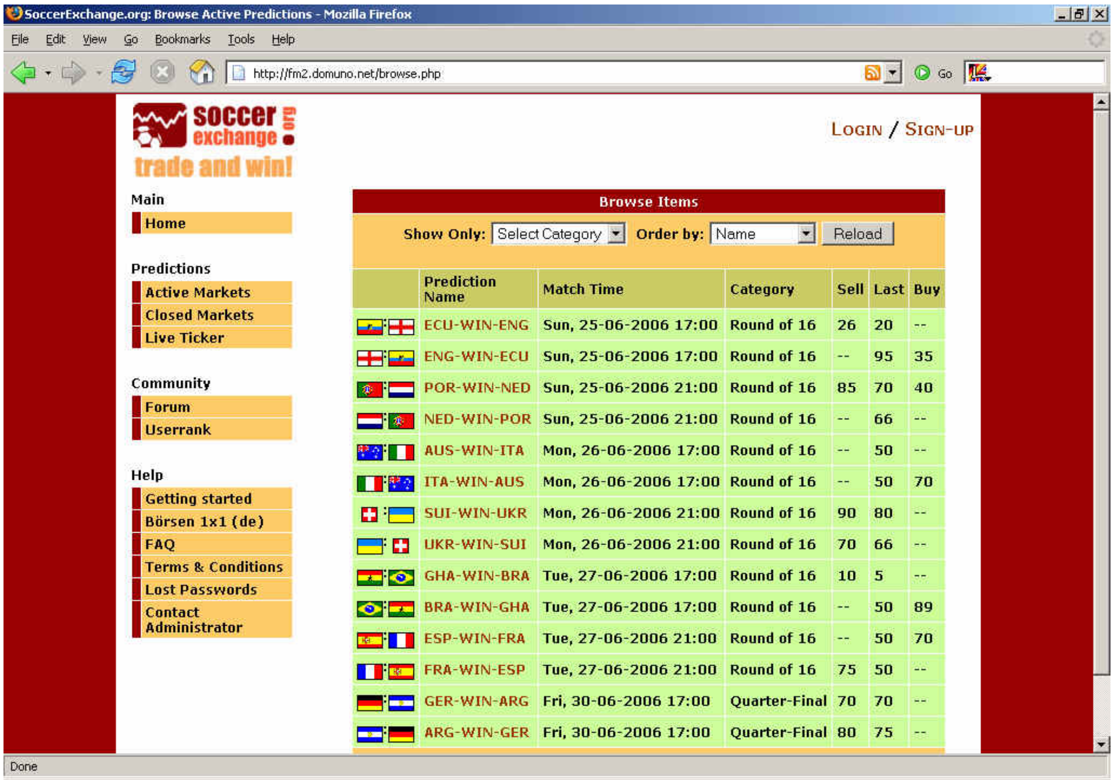


Figure 0.2: Listing shares

Fig 0.3 shows the live ticker which shows a list of last orders and transactions, containing information about share symbol, transactions date, quantity and price, updated every 60 seconds and played a sound for every new order/transaction.

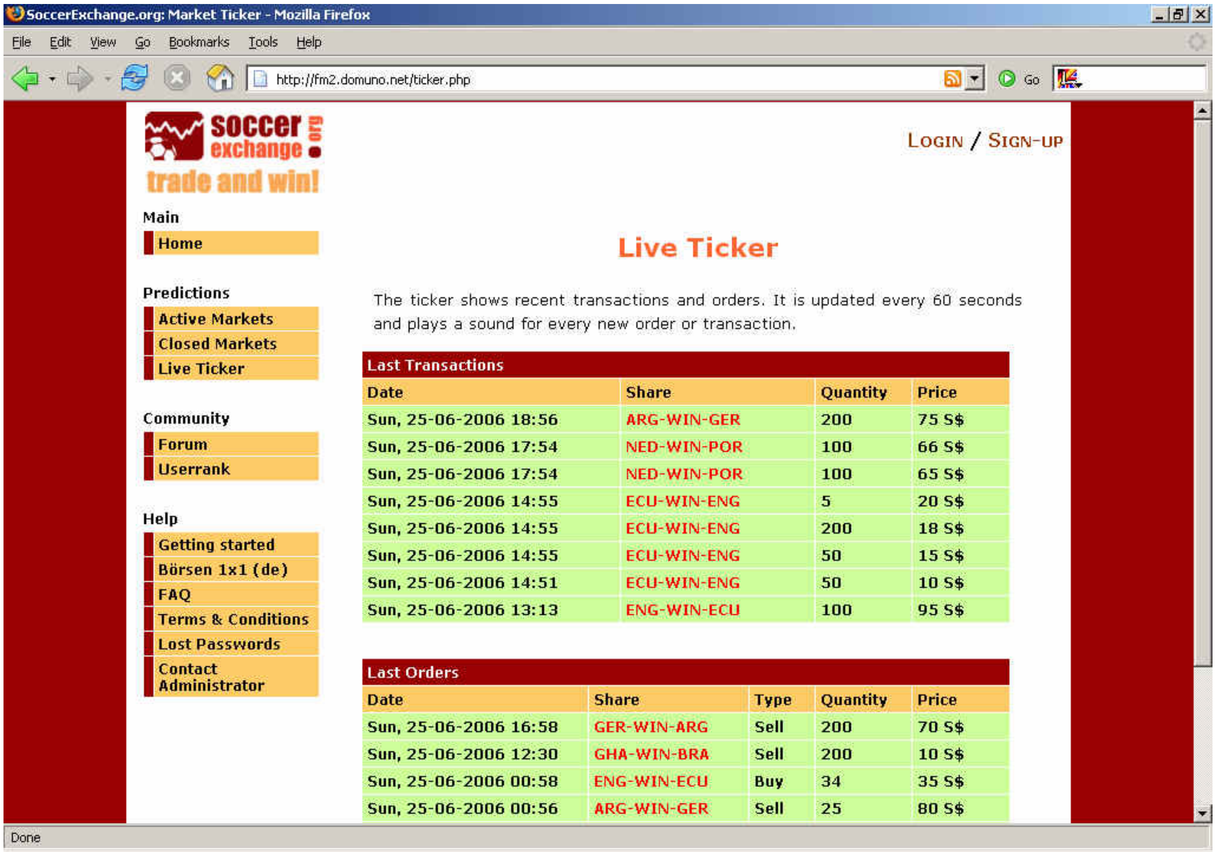


Figure 0.3: Live Ticker

Fig. 0.4 shows the contract profile view of an exemplary share. The listed information included besides the underlying soccer team and opposing team information about the arbitration date, last price, best outstanding bid/ask price, volume of shares in the market and corresponding portfolio. The profile included also links to popular sports websites that offered a considerable amount of media coverage about the sports events. In addition, a discussion forum for asking questions about trading was offered to traders.

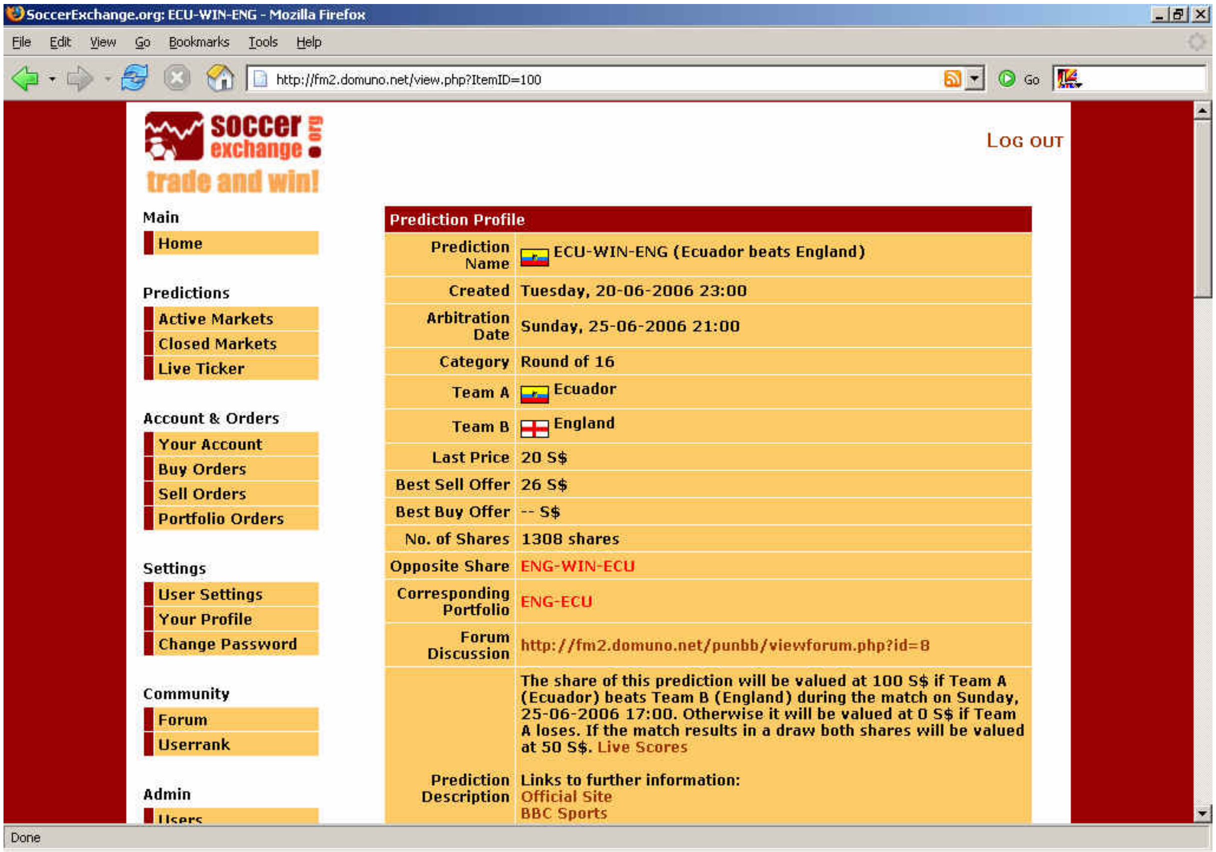


Figure 0.4: Contract Profile

Fig. 0.5 depicts the order screen that was included below the contract profile. The trader saw listed its current holdings of the contract and outstanding orders of the contract that could be deleted any time when desired. In addition, there was a form for creating a new buy or sell order. The form included a questionnaire that could be filled out and submitted along with the order type, quantity and limit price. Respondents were asked to state whether they have any for the contracts' underlying soccer team or the opposite team. In addition they were asked to give a direct probability estimate and to state the source of information used for making the probability estimate.

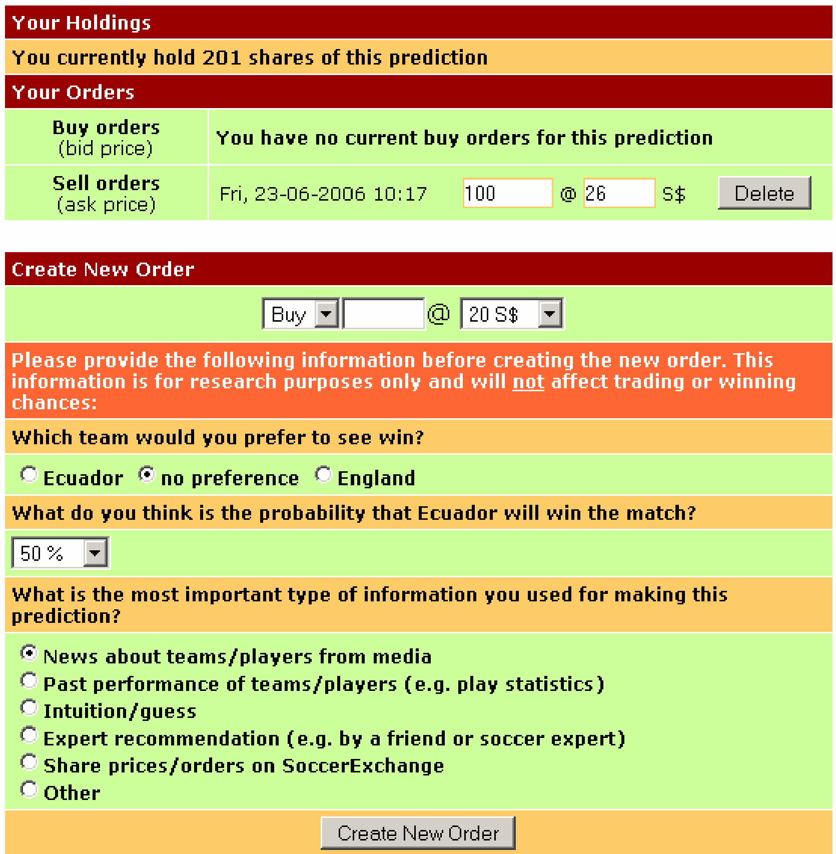


Figure 0.5: Order Screen

Fig. 0.6 shows the order queue with submitted limit prices and quantities and price history screen which was included in the contract view was well. The best outstanding buy and sell orders were listed at the top of the queue. Below the order queue was included a graph of the contract price history as well as a list showing date, price, quantity absolute/relative price change of historic transactions.

The portfolio view (Fig. 0.8) showed the profile of each portfolio and could be selected from a list of portfolios (Fig. 0.7). It included a description, the symbols of included contracts, the unit price (which was usually at 100$) and current holdings of the respective portfolio by the trader (which was usually min{holdings of included share A, holdings of included share B}).

Fig. 0.9 and 0.10 show screenshots of the trader account page. This page gives an overview over the traders' cash holdings, the free cash available for making purchase orders, the total market value of holdings (contract holdings valued at current market prices), the total account value (market value of contracts + cash), the account performance (increase/decrease of total account value since registration).

Furthermore, the account view showed a list of current held contracts with quantity, current price and total value of holdings. The account view included also a graph showing the historical account value and a list of historical transactions.

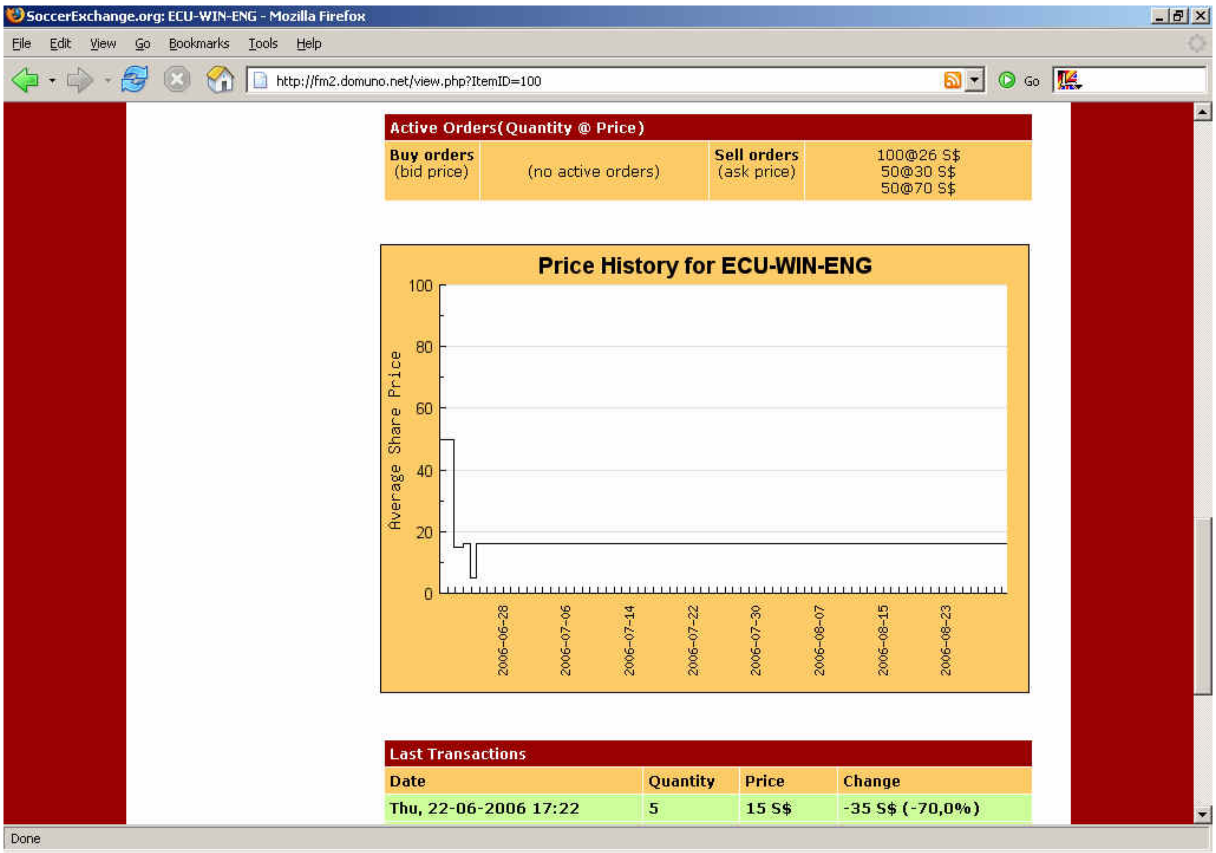


Figure 0.6: Order Queue and Historical Price Chart/List

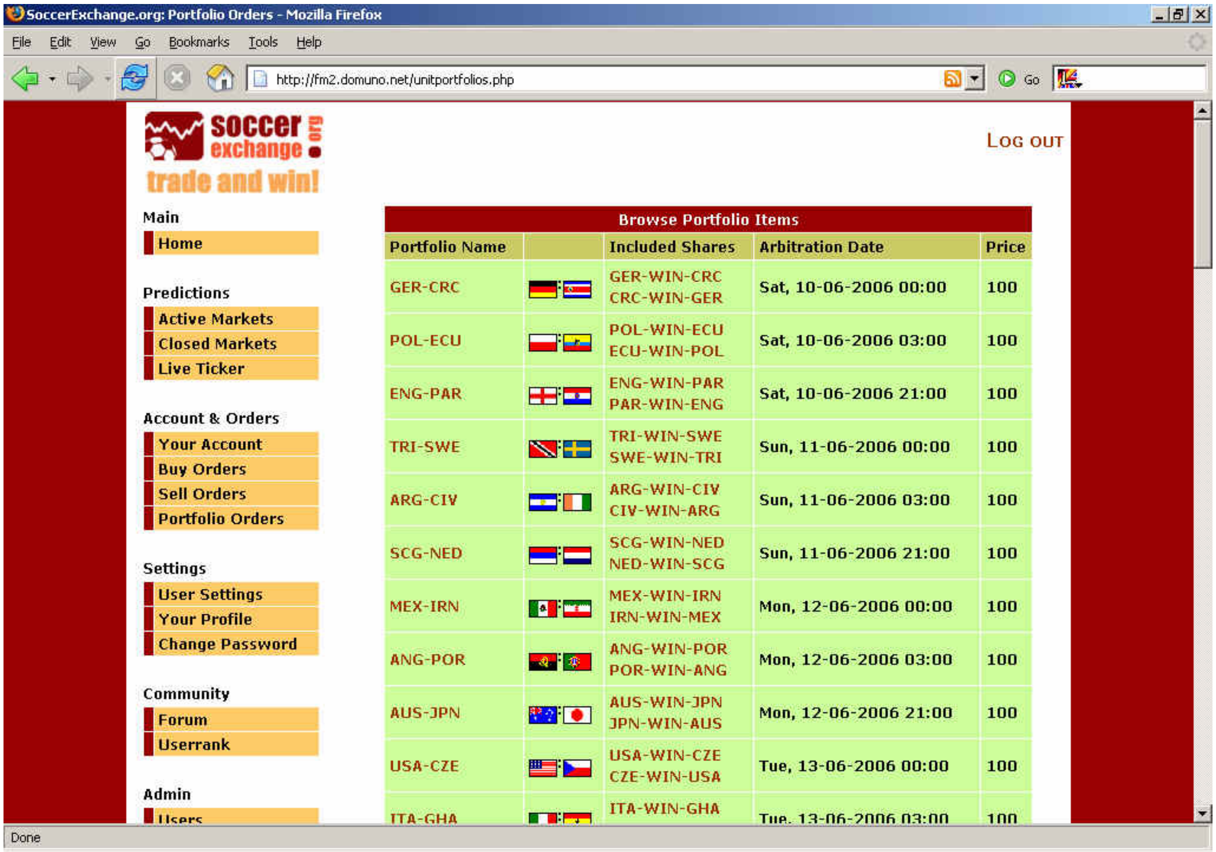


Figure 0.7: Portfolio Listing

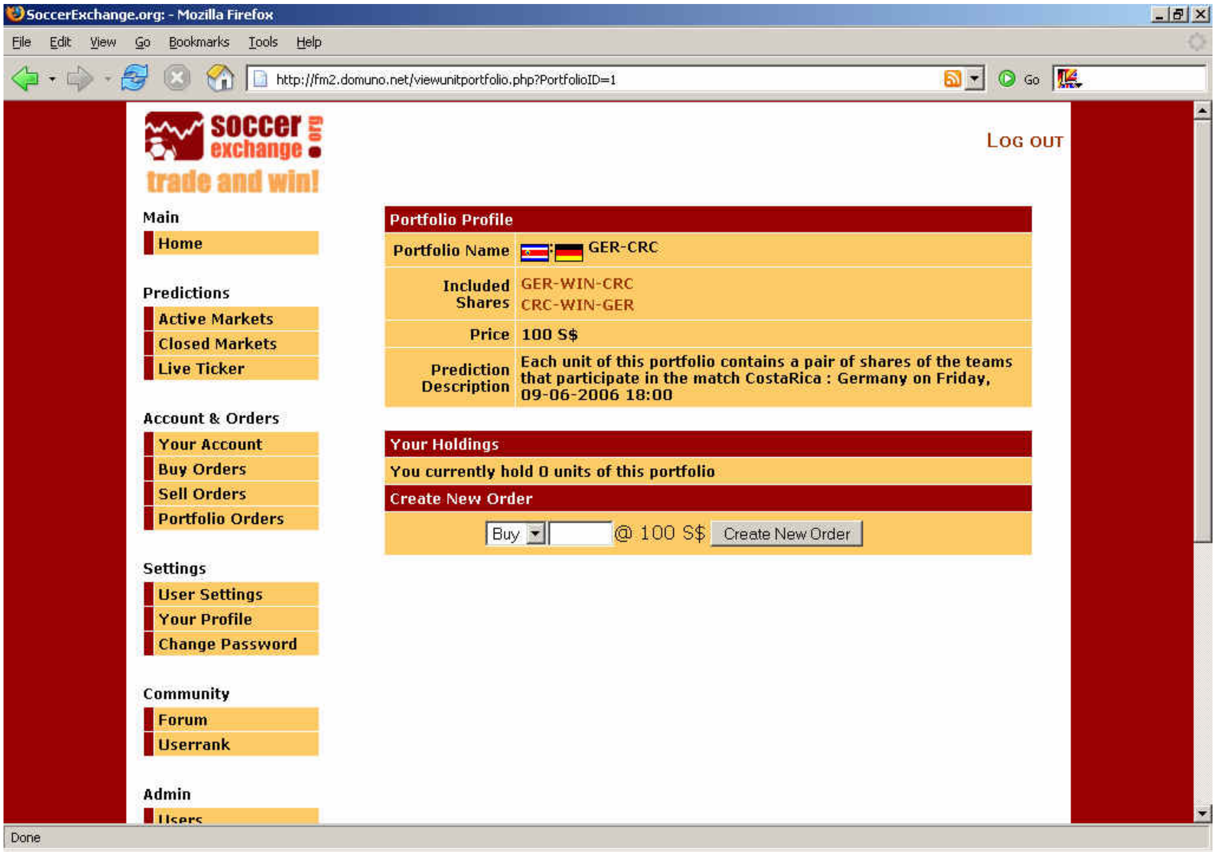


Figure 0.8: Portfolio Order Screen

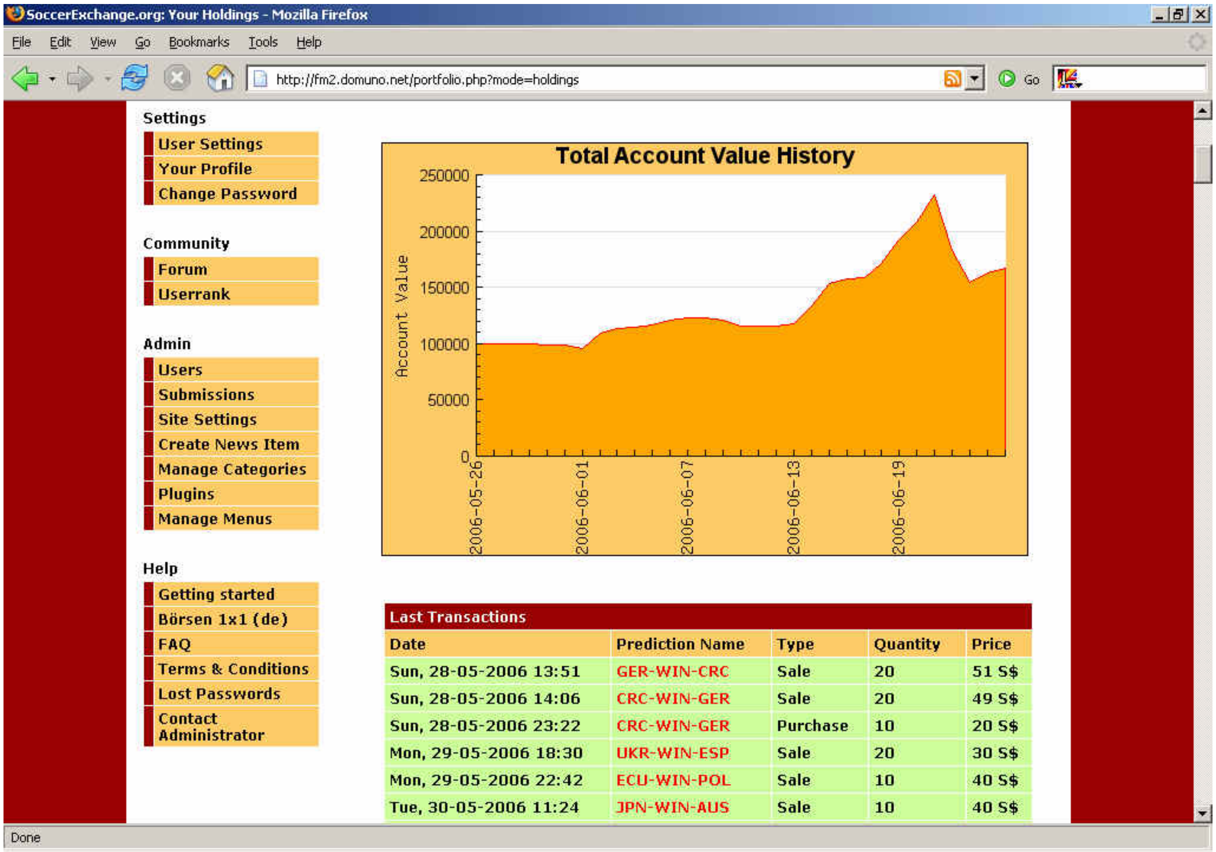


Figure 0.9: Account Value and Transaction History

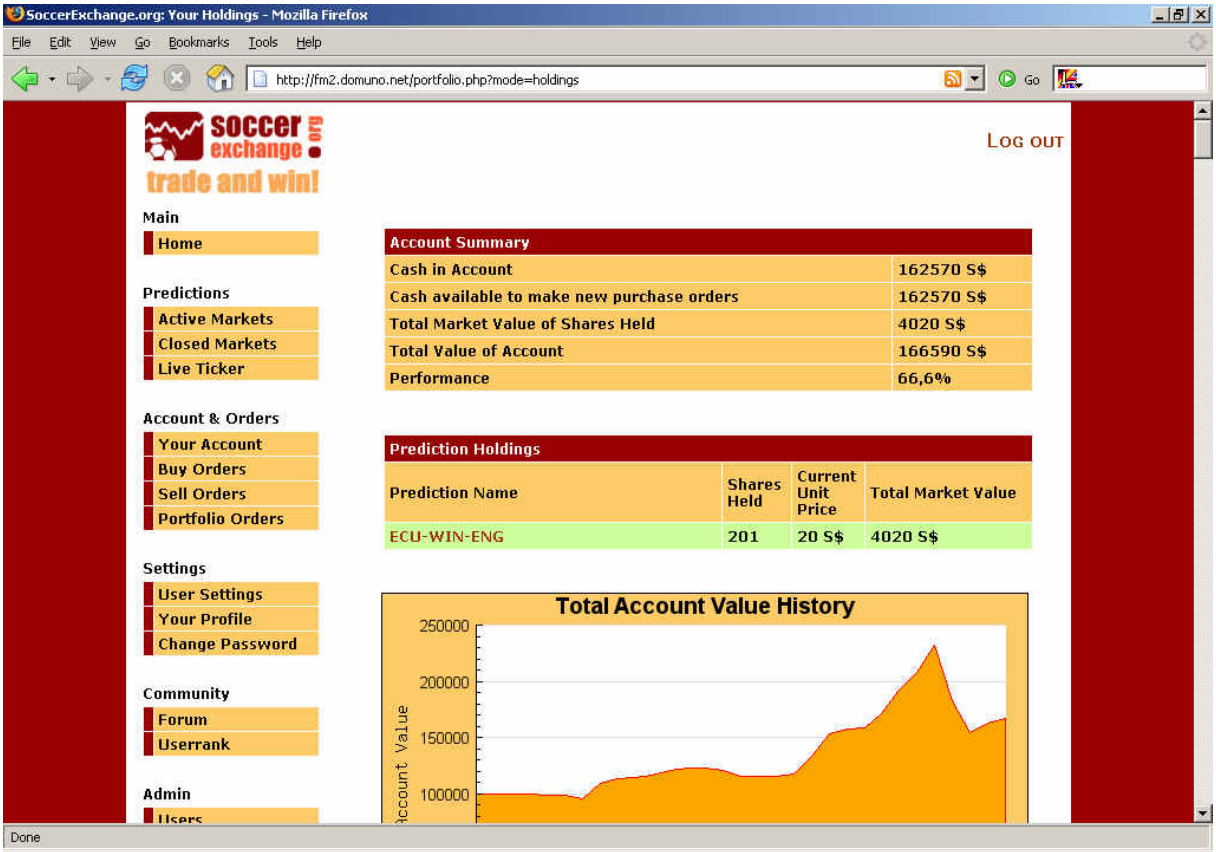


Figure 0.10: Account Information and Statistics

Fig. 0.11 depicts the userrank page which listed all traders according to account value performance.

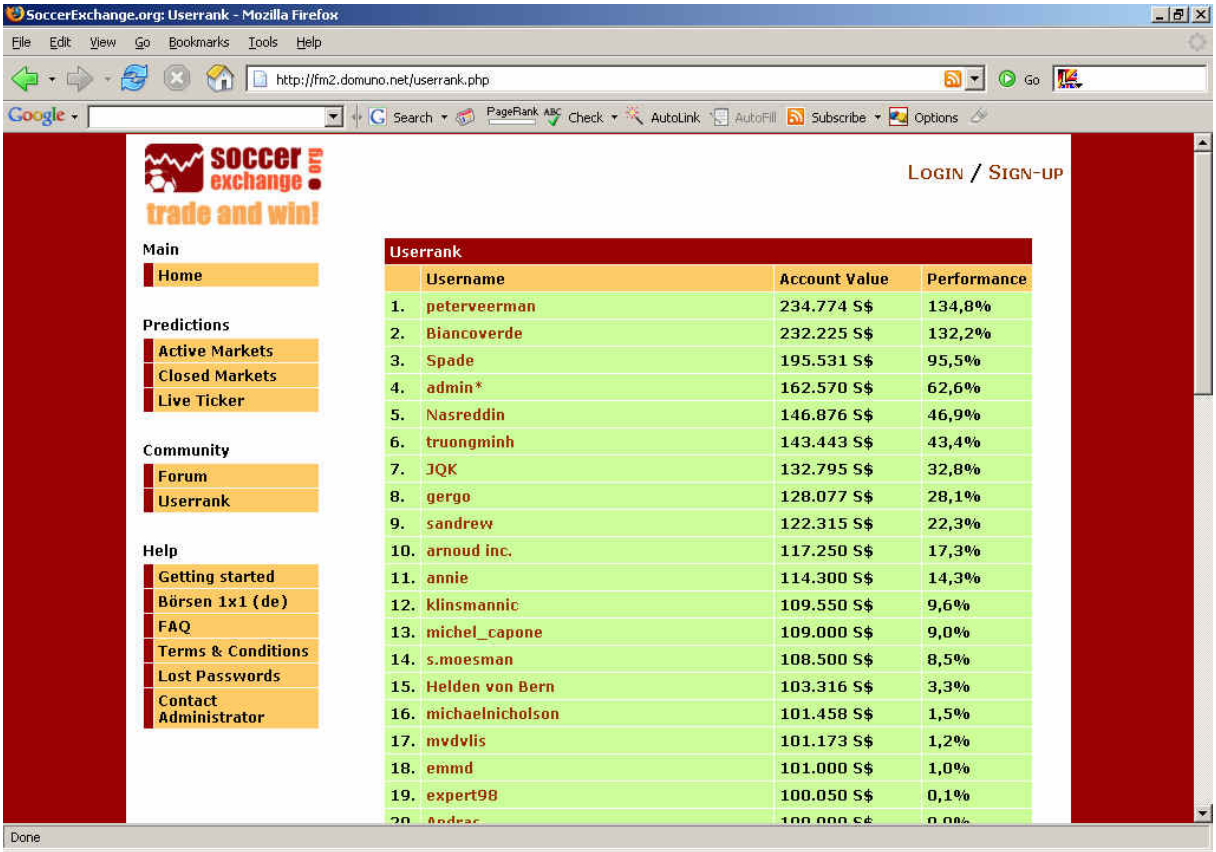


Figure 0.11: Userrank

B Trader Manual

The following sections shows the manual that was used to educate traders

Getting Started

What is SoccerExchange?

SoccerExchange is a virtual prediction market and is like a stock market. It uses the power of market forces to aggregate information from different individuals to create a more accurate prediction of events. From the user's perspective, this site functions as a game in which individuals can test their savvy for prediction against other users.

Before starting, please read carefully the terms and conditions

What kinds of shares are offered in this stock market?

The shares offered on SoccerExchange are tied to the outcome of world cup soccer matches. For each soccer team and each match a diffrent share is offered. For example, the share with the symbol NED-WIN-ARG will be tied to a final payoff if The Netherlands beat Argentina. But there is also a share ARG-WIN-NED that pays off if Argentina wins.

How is the payoff determined?

If a team wins the holder of the corresponding share will get a payoff of 100S$ otherwise he will get nothing. Usually 6 hours after the scheduled match the market will be closed, the bank will get all shares back and the holder will get credited the final payoff as cash on his account (either 100 S$ or 0 S$ for each share). This date is called "arbitration date".

What happens if the game ends in a draw?

If a definite winner cannot be determined the final payoff will be 50 S$ each for the shares of both teams.

How can I trade shares?

You can buy or sell each share on the market from or to other traders prior to the arbitration date. You can place a buy or sell order by entering a limit buying or selling prices (called bid or ask). Whether the order is executed immediately depends on whether there are sale or purchase offers from other users whose limit prices fit your offered price.

Why do the prices reflect probabilities?

Since the payoff is 100S$ if the event of a share takes place and nothing if not the market mechanism forces you to offer and demand shares at prices that equal your expectations about the probability of that event. If you think that team A will win with 80% probability you will be likely to pay maximal 80S$ for its underlying share. However, you may try to buy it at a lower price in order to make a trading profit.

Do I have to use real money?

No, after registration you will get a free account with 100.000 SoccerDollar from the bank. This is the virtual currency you use for trading shares. However, the traders with the highest trading profits will win prizes at the end.

What are the prizes?

1. price: 1 Amazon gift certificate worth 100 Euro
2. price: 1 Amazon gift certificate worth 60 Euro
3. price: 1 Amazon gift certificate worth 40 Euro

What options do I have to buy shares?

1) The first option is to place a buy order with a limit buy price as mentioned. However, if there are not enough shares offered for sale or if the offered sale prices do not fit your desired purchase price you have to wait until your order is matched by another subsequent order.

2) The second possibility is to buy a portfolio. You can buy portfolios immediately at any time from the bank.

What is a portfolio?

A portfolio contains usually a pair of shares from team A and the opposite team B as well. It is offered for a fixed price of 100 S$ and can be purchased and sold any time from and to the bank. Foer example, NED-ARG is a portfolio that contains the shares NED-WIN-ARG (The Netherlands win) and ARG-WIN-NED (Argentina wins). If you hold a portfolio until the closure of the market you will neither lose nor gain money regardless of which team wins since you get 100S$ for one of the two shares for sure!

Why should I buy portfolios if I want to get only the shares of team A but not team B?

At the beginning of the game there may be no shares in the market to offer for sale but many buy orders. So, you may not be able to buy shares of your favorite team. The only way to get shares of team A immediately is to buy a bundle for 100 S$ and to sell the shares of team B on the market. If team A wins you will earn 100 S$ + the sale price of share B and make a profit.

Buying portfolios and selling its included shares is the only way to get shares in circulation to the market! So if you only place buy orders and don't buy portfolios and offer shares for sale you may never get your desired shares!

How can I buy and sell a portfolio?

Select under "Order Portfolios" a portfolio by clicking on the symbol and enter a quantity. You will then get a share of team A and B at a time times the quantity. If you want to sell units of a portfolio you need to hold at least one pair of shares of team A + team B. If you hold shares of one only team or if all shares of one team are bounded to sell orders you cannot sell portfolios!

How can I place a buy or sell order for a share?

1) Select the appropriate share under "Active Markets"
2) Enter a buy/sell limit price (the maximum price our are willing to pay for buying a share or the minimum price you are asking for selling a share)

3) Select the quantity of shares

4) Fill in the questionnaire below and submit your order

Why do I have to fill in a questionnaire along with every order?

This questionnaire is for research purposes only and doesn't influence your trading or winning chance.

How is an order processed?

If your buy or sell order matches an outstanding sell or buy order it will be executed immediately. This happens usually if your limit buy/sell price is equal or above/below the highest/lowest outstanding limit sell/buy price by another trader. In other words, if you are a buyer you need to offer a higher or equal price than proposed by the seller and vice versa. Otherwise, if your offered purchase price is lower, your order will be added to a queue as an outstanding order until it gets matched by a subsequent order. You see usually the best (highest) outstanding bid price and the best (lowest) outstanding ask price at the top of the queue. If the quantity of your order matches only a part of a fitting outstanding order it will be executed partially and the remaining order will be added to the queue.

The following example will illustrate this:

In the following example, there are 79 sell orders in the queue for an ask price of 50 S$.

We enter a buy order with 80 shares for a maximum purchase price (bid) of 52 S$.

Since our bid price matches the ask price of the existing order it will be executed immediately for 79 shares at 50 S$. However, there would be 1 buy order at 52$ left open and added to the queue.

Note: Own sell orders cannot be matched by own buy orders and vice versa. Instead, such orders will be added to the queue until matched by orders of other users. Orders can only be processed and executed if enough cash is available. After each transaction you will receive an email confirmation with relevant details (unless you have not deactivated that functionality under "User Settings"). In contrast to real stock exchanges all transactions and account maintenance on SoccerExchange are free of charge.

Trading tips

Let us take an example for illustration of a trading situation: Assume that you are sure that Brazil will beat Switzerland in a match. Then, you could buy a portfolio for 100 S$ containing a pair of shares from both teams and try to sell the Switzerland share. For instance, there could be a Switzerland fan who is willing to pay you 20 S$ because he believes that the Swiss have at least a 20%-chance to win. If Brazil wins, you will make 20 S$ profit (100 S$ final value of the Brazil share + 20 S$ selling price of the Switzerland share - 100 S$ portfolio price) or 20% of your investment. The Switzerland fan would make a loss of 20 S$ or 100% of his investment. However, if Switzerland wins unexpectedly you will loose 80 S$ (0 S$ final value of the Brazil share + 20 S$ selling price of the Switzerland share - 100 S$ portfolio purchasing price) or 80% of your investments. The Switzerland fan will make 80 S$ profit (100 S$ final value of the Brazil share - 20 S$ purchase price for the Brazil share) or 300%! of his investment.

This example shows that you will risk much if you hold only shares on one team. On the other hand you can gain much by buying at very low prices given that the underlying team finally wins. Your trading strategy should take into account your confidence about your prediction. You can limit your risk by purchasing shares of both teams at prices close to

50 S$ or diversifying by holding several shares of diffrent matches and teams. However, please note that it makes no sense to buy shares of both competing teams at 50 S$ or portfolios with both teams and to wait until the market get closed. You will then get only as much as you have invested without any profit or loss.

It is only by trading that you can make profits!

How is the game organized?

The shares for the first round of the championship are offered right from the beginning. The shares for the matches of the second round will be offered as soon as the participating teams are known.

Have good luck and fun with trading!

C Software

C.1 Choice of trading platform software

The trading platform of SocerExchange was built upon open source software. The author identified 3 different open source packages that were available.

Zocalo[28]
A prediction market software written in Java and based upon object orientated language. Zocalo has been created for the purpose of running short-session experimental markets but is not appropriate for conducting long term prediction markets with a time period of more than one day. Therefore it wasn't considered for this research.

IdeaFutures[29]
Ideafutures is software package that emerged from the popular Ideafutures prediction markets which claim on future developments. It is written in Perl programming language. It wasn't considered for this research as it didn't use a relational database but only log files instead. In addition, the author wasn't familiar with Perl.

FreeMarket Project[30]
Freemarket is a recent development based on PHP and procedural programming. It uses a relational MySQL database. The author chose this package for his research because of his familiarity with PHP and because it allowed easy customization. The software needed extensive modifications before it could be used for this research. Portfolios were introduced

[28] http://sourceforge.net/projects/zocalo/

[29] http://sourceforge.net/projects/ideafutures/

[30] http://www.freemarket-project.org

C.2 Database Architecture

Fig. 0.12 shows a relational schema of the database structure with the most important tables and fields (including data types). New outstanding orders were added to the respective table. Transactions and orders were recorded in separate tables. The orders table contained only records of outstanding orders that didn't match immediately with other orders. When they were matched subsequently, the table entry of the respective order was deleted from the orders table and a new transaction entry was added to the transactions table containing the ID's of the previous orders that led to the transaction. When the outstanding order was cancelled by the trader, it was simply deleted from the "orders" table. All orders were also logged into a logfile together with the questionnaire data so that historical data were also kept recorded. that was later transformed to MySQL database for data processing. If a transaction resulted in a purchase of a contract the new contract holdings were added to the respective holdings table.

The "portfolios" table included a list of unique portfolios. Portfolio transactions as such were not recorded but only the transactions of the included shares. The portfolio id of the portfolio to which a contract belonged was recorded for each contract in the "shares" table. If a portfolio was selected by the trader for purchase or sale the included shares were looked up in the "shares" table and transaction executed at a standard price of 50 S$ (since the sum of a portfolio unit transaction summed up to a price of 100 S$).

The "users" table contained besides basic information about users also the historical account values that were updated every day to and added to a queue. It also contained a field of current total account value that was updated with every transaction.

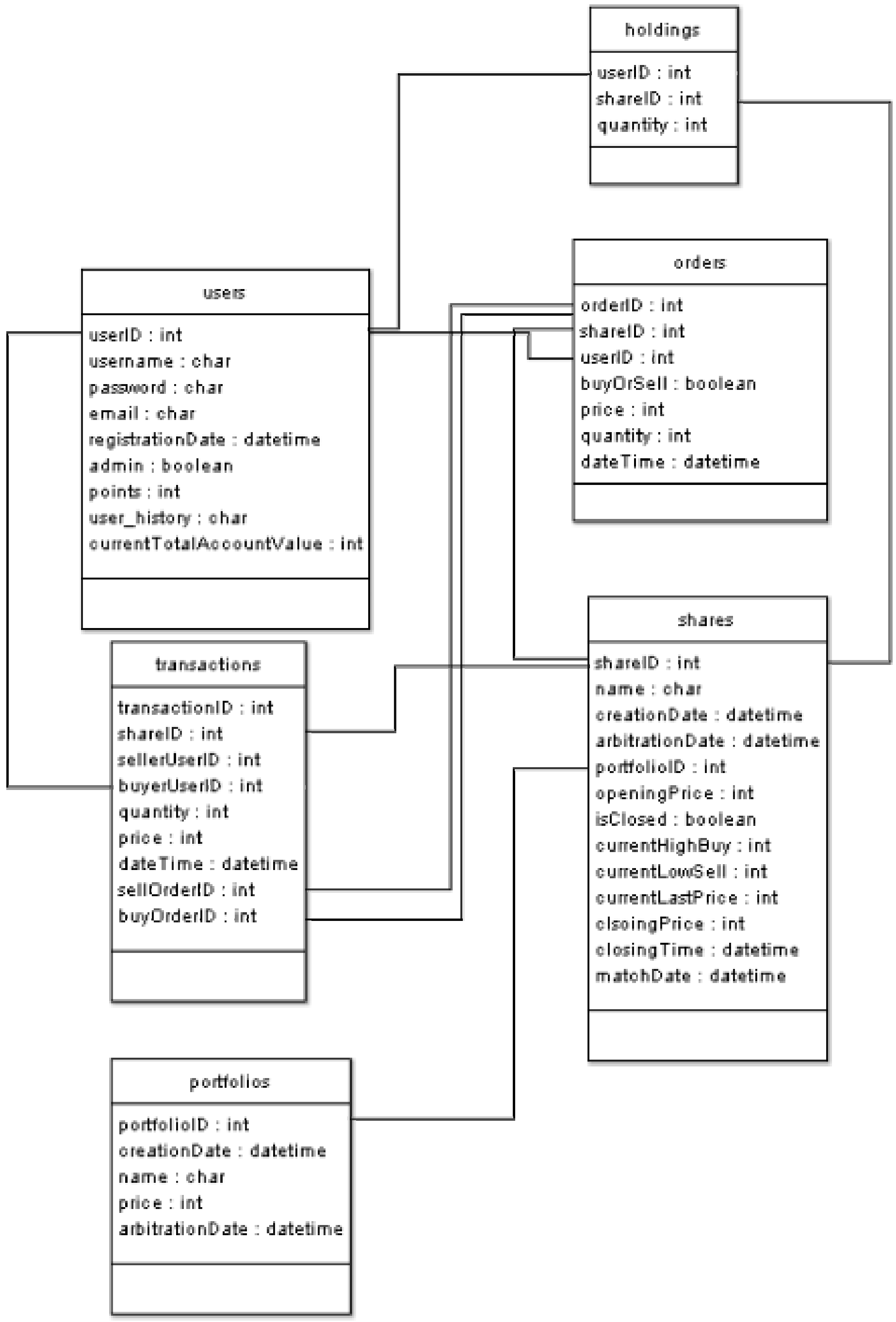


Figure 0.12: Database structure

D Description of the datasets and data pre-processing

Introduction

There are 5 tables relevant for the analysis: orders, orders_bmd transactions, transactions_bmd and items.
The final calculation have been performed in the excel worksheet soccerexchange_results.xls
The rough datasets (sql, csv) and excel sheets (xls) can be downloaded via http://www.soccerexchange.org/data

Table orders:

field	description
date	
newdel	1=new order, 0=delete old order
id	each new order gets a new id, delete orders contain the id of the original order
user	user id
item	share id
type	1=buy order, 0=sell order
quant	quantity
price	buy order= maximum order price, sell order=minimum order price
prob	probability estimate - via questionnaire
pref	preference for a team (1=team A - the shares' corresponding team, 2=no preference, 3=team B - the shares' opposite team) - via questionnaire
source	source of information (1=News about teams/players from media,2=Past performance of teams/players (e.g. play statistics),3=Intuition/guess,4=Expert recommendation (e.g. by a friend or soccer expert),5=Share prices/orders on SoccerExchange,6=Other) - via questionnaire

Table transactions

date

id	each new transaction gets a new id
buyer	user id of the buyer
buyorder	order id od the corresponding buy order
seller	user id of the seller
sellorder	order id od the corresponding sell order
item	share id
quantity	transaction quantity
price	transaction price

Table items

id	share id
name	country code e.g. GER-WIN-CRC=Germany beats Costa Rica
date	creation date (market opening)
category	1=pre-round, 2=Round of 16, 3=quarter final, 4=half final, 5=3rd place, 6=final
closingprice	determined final price=final payoff
closingtime	closing date
winner	corresponding team of the share
loser	corresponding opposite team of the share
matchdate	

Transformation of Tables

In order to create a table with all orders submitted prior to the match date (orders_bmd) the original table orders was copied and the following SQL query was run:

```
Delete FROM orders_bmd USING orders_bmd, items WHERE items.id=orders_bmd.item
AND unix_timestamp(orders_bmd.date)>unix_timestamp(items.matchdate)
```

In order to create a table with all transactions executed prior to the match date (transactions_bmd) the original table transaction was copied and the following SQL query was run:

```
Delete FROM transactions_bmd USING transactions_bmd, items WHERE
items.id=transactions_bmd.item AND
unix_timestamp(transactions_bmd.date)>unix_timestamp(items.matchdate)
```

SQL Queries for Obtaining Trader Statistics Data

Counting number of marginal trades per user (rule I: order submitted but not matched immediately though matched later during a day before midnight)

```
SELECT orders_bmd.user, Count( * ) FROM orders_bmd JOIN transactions_bmd ON
(transactions_bmd.buyorder=orders_bmd.id OR
transactions_bmd.sellorder=orders_bmd.id) WHERE
transactions_bmd.date>orders_bmd.date AND
dayofyear(transactions_bmd.date)=dayofyear(orders_bmd.date) GROUP BY
orders_bmd.user
```

Selecting marginal trades (rule 2: II orders submitted but not matched immediately though within +-5% of the last trading price)

```
Found no solution
```

Counting number of orders per user

```
SELECT orders_bmd.user, Count( * )
FROM orders_bmd
GROUP BY orders_bmd.user
```

Counting order volume (quantity) per user

```
SELECT orders_bmd.user, SUM(orders_bmd.quant)
FROM orders_bmd
GROUP BY orders_bmd.user
```

Counting order volume (quantity*price) per user

```
SELECT orders_bmd.user, SUM(orders_bmd.quant*orders_bmd.price)
FROM orders_bmd
GROUP BY orders_bmd.user
```

Counting number of transactions per user (excluding portfolio transactions)

```
SELECT orders_bmd.user, Count( * )
FROM orders_bmd
JOIN transactions_bmd ON ( transactions_bmd.buyorder = orders_bmd.id
OR transactions_bmd.sellorder = orders_bmd.id ) WHERE transactions_bmd.seller<>0
AND transactions_bmd.buyer<>0
GROUP BY orders_bmd.user
```

Counting transactions volume per user (quantity * price - excluding portfolio transactions)

```
SELECT orders_bmd.user, SUM(transactions_bmd.quant*transactions_bmd.price)
FROM orders_bmd
JOIN transactions_bmd ON ( transactions_bmd.buyorder = orders_bmd.id
OR transactions_bmd.sellorder = orders_bmd.id ) WHERE transactions_bmd.seller<>0
AND transactions_bmd.buyer<>0
GROUP BY orders_bmd.user
```

Counting portfolio transactions per user

```
SELECT users.user_id, Count( * )
FROM users
JOIN transactions_bmd ON ( transactions_bmd.buyer = users.user_id
```

```
OR transactions_bmd.seller = users.user_id) WHERE transactions_bmd.seller=0 OR
transactions_bmd.buyer=0
GROUP BY users.user_id
```

Counting number of trades with a preference for either team A or B per trader (excluding non valid entries, non-valid-entry=questionnaire form with fields in initial setting: orders_bmd_ve.pref=2 AND orders_bmd_ve.prob=50 AND orders_bmd_ve.source=1)

```
SELECT orders_bmd, Count( * )
FROM orders_bmd
JOIN transactions_bmd ON ( transactions_bmd.buyorder = orders_bmd.id
OR transactions_bmd.sellorder = orders_bmd_ve.id )
WHERE (orders_bmd.pref=1 or orders_bmd.pref=3) AND NOT(orders_bmd.pref=2 AND
orders_bmd.prob=50 AND orders_bmd.source=1)
Group BY orders_bmd.user
```

Counting number of trades with no preference for either team A or B per trader (excluding non valid entries, non-valid-entry=questionnaire form with fields in initial setting: orders_bmd_ve.pref=2 AND orders_bmd_ve.prob=50 AND orders_bmd_ve.source=1)

```
SELECT orders_bmd, Count( * )
FROM orders_bmd
JOIN transactions_bmd ON ( transactions_bmd.buyorder = orders_bmd.id
OR transactions_bmd.sellorder = orders_bmd_ve.id )
WHERE (orders_bmd.pref=2) AND NOT(orders_bmd.pref=2 AND orders_bmd.prob=50
AND orders_bmd.source=1)
Group BY orders_bmd.user
```

Counting number of trades with source=1-6 per user (only valid entries)

```
SELECT orders_bmd.user, Count( * )
FROM orders_bmd
JOIN transactions_bmd ON ( transactions_bmd.buyorder = orders_bmd.id
```

```
OR transactions_bmd.sellorder = orders_bmd.id )
WHERE (orders_bmd.source=1) AND NOT(orders_bmd.pref=2 AND
orders_bmd.prob=50 AND orders_bmd.source=1)
Group BY orders_bmd.user
```

Prediction accuracy (absolute mean error) of users (only valid entries)

```
SELECT orders_bmd.item, avg( abs( orders_bmd.prob - items.closingprice ) )
FROM transactions_bmd
JOIN orders_bmd ON ( transactions_bmd.buyorder = orders_bmd.id
OR transactions_bmd.sellorder = orders_bmd.id )
JOIN items ON ( items.id = orders_bmd.item ) WHERE NOT(orders_bmd.pref=2 AND
orders_bmd.prob=50 AND orders_bmd.source=1)
GROUP BY orders_bmd.user
```

Count number of days with marginal trades per each user

```
SELECT orders_bmd.user, Count( DISTINCT (
dayofyear( orders_bmd.date ) ) )
FROM orders_bmd
JOIN transactions_bmd ON ( transactions_bmd.buyorder = orders_bmd.id
OR transactions_bmd.sellorder = orders_bmd.id )
WHERE transactions_bmd.date > orders_bmd.date
AND dayofyear( transactions_bmd.date ) = dayofyear( orders_bmd.date )
GROUP BY orders_bmd.user
```

Profit for each trader=Purchases (valued at closing price – purchasing price) + Sales (valued at selling price – final price)

Purchases

```
Select transactions_bmd.buyer, SUM(transactions_bmd.quantity*(items.closingprice-
transactions_bmd.price)) FROM transactions_bmd JOIN items ON (items. id =
```

```
transactions_bmd.item) WHERE transactions_bmd.date<items.matchdate GROUP BY
transactions_bmd.buyer
```

Sales

```
Select SUM(transactions_bmd.quantity*(transactions_bmd.price- items. closingprice))
FROM transactions_bmd JOIN items ON (items. id = transactions_bmd.item) WHERE
transactions_bmd.date<items.matchdate GROUP BY transactions_bmd.seller
```

SQL Queries for Obtaining Market Statistics Data

Markets with most valid entries (transactions with corresponding orders whose questionnaires were filled out)

```
SELECT COUNT(Distinct(transactions_bmd.id))
FROM transactions_bmd
JOIN orders_bmd ON ( transactions_bmd.buyorder = orders_bmd.id
OR transactions_bmd.sellorder = orders_bmd.id ) WHERE NOT(orders_bmd.prob=50
AND orders_bmd.pref=2 AND orders_bmd.source=1)
GROUP BY transactions_bmd.item
```

=> these figures have to be subtracted from the number of all transactions per market

Transactions per market (including portfolio transactions)

```
SELECT COUNT(DISTINCT(transactions_bmd.id)) FROM transactions_bmd Group by
transactions_bmd.item
```

Transactions per market (excluding portfolio transactions)

```
SELECT transactions_bmd.item, COUNT(DISTINCT(transactions_bmd.id)) FROM
transactions_bmd WHERE transactions_bmd.seller<>0 AND transactions_bmd.buyer<>0
Group by transactions_bmd.item
```

Transactions volume per market (including portfolio transactions)

```
SELECT transactions_bmd.item,
SUM(transactions_bmd.quantity*transactions_bmd.price) FROM transactions_bmd
Group by transactions_bmd.item
```

Quantity of traded shares per market (excluding portfolio transactions)

```
SELECT transactions_bmd.item, SUM(transactions_bmd.quantity) FROM
transactions_bmd WHERE transactions_bmd.seller<>0 AND transactions_bmd.buyer<>0
Group by transactions_bmd.item
```

Active traders per market (at least 1 order submitted)

```
SELECT orders_bmd.item, COUNT(DISTINCT(orders_bmd.user)) FROM orders_bmd
Group by orders_bmd.item
```

Trading Days per Market

```
SELECT fm_items.item_id, (dayofyear(fm_items. item_closingtime)-
dayofyear(fm_items.item_date)+1)
GROUP BY fm_items.item_id
```

Last trading and closing price of each market

See www.soccerexchange.org => closed markets

Selecting Orders & Transactions for construction supply & demand

```
SELECT * FROM orders_bmd WHERE orders_bmd.item=x AND orders_bmd.newdel=1
```

```
SELECT * FROM transactions_bmd WHERE transactions_bmd.item=x AND
transactions_bmd.buyer<>0 AND transactions_bmd.seller<>0
```

Calculating mean Average prediction error of all traders per market

```
SELECT orders_bmd.item, avg( abs( orders_bmd.prob - items.closingprice ) )
FROM transactions_bmd
JOIN orders_bmd ON ( transactions_bmd.buyorder = orders_bmd.id
OR transactions_bmd.sellorder = orders_bmd.id )
JOIN items ON ( items.id = orders_bmd.item ) WHERE NOT(orders_bmd.pref=2 AND
orders_bmd.prob=50 AND orders_bmd.source=1)
GROUP BY orders_bmd.item
```

Calculating mean Average prediction error of all traders per market

```
SELECT orders_bmd.item, avg( orders_bmd.prob )
FROM transactions_bmd
JOIN orders_bmd ON ( transactions_bmd.buyorder = orders_bmd.id
OR transactions_bmd.sellorder = orders_bmd.id )
JOIN items ON ( items.id = orders_bmd.item ) WHERE NOT(orders_bmd.pref=2 AND
orders_bmd.prob=50 AND orders_bmd.source=1)
GROUP BY orders_bmd.item
```

Number of individual predictions per market

```
SELECT Count(orders_bmd.id), avg( abs( orders_bmd.prob - items.closingprice ) )
FROM transactions_bmd
JOIN orders_bmd ON ( transactions_bmd.buyorder = orders_bmd.id
OR transactions_bmd.sellorder = orders_bmd.id )
JOIN items ON ( items.id = orders_bmd.item ) WHERE NOT(orders_bmd.pref=2 AND
orders_bmd.prob=50 AND orders_bmd.source=1)
GROUP BY orders_bmd.item
```

Mean absolute forecast accuracy according to utilized sources

```
SELECT orders_bmd.source, count(orders_bmd.id), avg(abs( orders_bmd.prob -
items.closingprice ) )
FROM transactions_bmd
JOIN orders_bmd ON ( transactions_bmd.buyorder = orders_bmd.id
OR transactions_bmd.sellorder = orders_bmd.id )
JOIN items ON ( items.id = orders_bmd.item ) WHERE NOT(orders_bmd.pref=2 AND
orders_bmd.prob=50 AND orders_bmd.source=1)
GROUP BY orders_bmd.source
```

Number of accurately predicted underdogs

```
SELECT orders_bmd.source, count(orders_bmd.id)
FROM transactions_bmd
JOIN orders_bmd ON ( transactions_bmd.buyorder = orders_bmd.id
OR transactions_bmd.sellorder = orders_bmd.id )
JOIN items ON ( items.id = orders_bmd.item ) WHERE NOT(orders_bmd.pref=2 AND
orders_bmd.prob=50 AND orders_bmd.source=1) AND (orders_bmd.prob<50 AND
items.closingprice=0)
GROUP BY orders_bmd.source
```

E Market results

E.1 Overview of Markets Results for the 128 Experimental Markets

Id	Trading days	Trans-actions	Quantity shares	Orders	Active traders	Trading volume	Last trading price	Closing price
1	14	14	374	56	16	98,250	95	100
2	14	43	2,153	88	16	122,378	20	0
3	14	2	210	7	5	28,800	75	0
4	14	7	250	14	8	22,100	50	100
5	15	6	221	28	13	77,070	60	100
6	15	12	751	34	9	78,710	50	0
7	15	10	315	28	11	23,940	4	50
8	15	4	32	20	6	24,997	95	50
9	15	10	180	22	8	38,320	95	100
10	15	9	335	20	9	30,300	2	0
11	16	10	245	29	10	43,000	15	0
12	16	13	600	36	10	83,100	95	100
13	16	3	90	7	5	14,700	80	100
14	16	5	80	14	5	9,740	20	0
15	16	2	80	7	4	11,400	5	0
16	16	3	35	11	8	14,025	75	100
17	17	6	150	12	8	33,970	85	100
18	17	6	310	12	7	24,250	20	0
19	17	4	165	11	5	15,440	30	0
20	17	6	135	16	7	21,015	80	100
21	18	8	424	23	12	71,468	85	100

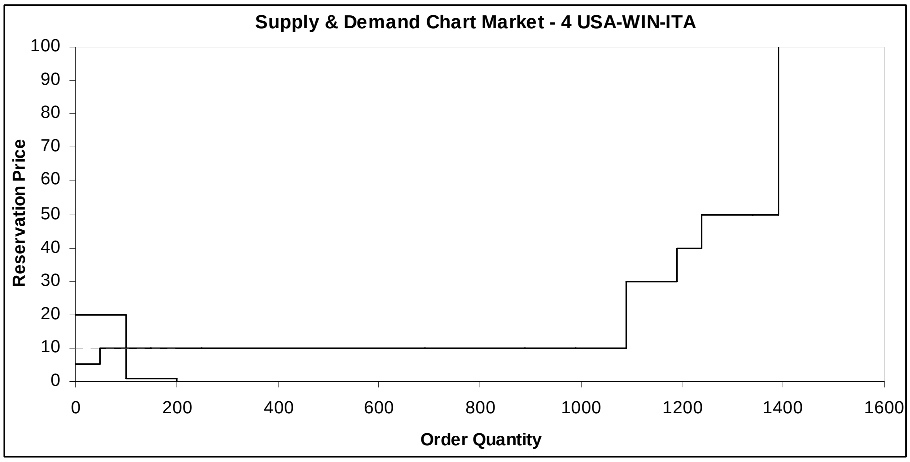
22	18	13	1,070	30	9	57,700	7	0
23	17	6	175	17	8	25,060	70	100
24	17	5	190	19	6	25,400	60	0
25	18	12	325	31	10	85,250	85	50
26	18	20	912	40	11	73,735	30	50
27	18	9	212	30	12	38,788	74	100
28	18	4	330	14	5	36,200	35	0
29	19	6	370	18	13	75,700	85	100
30	19	7	390	17	11	52,050	20	0
31	19	3	60	8	5	17,950	80	50
32	19	3	109	9	5	14,485	15	50
33	19	4	365	12	6	53,550	90	100
34	19	3	110	7	4	23,850	20	0
35	20	4	95	9	5	13,550	75	100
36	20	4	80	9	5	8,500	10	0
37	20	5	150	13	9	41,000	95	100
38	20	8	470	16	7	31,450	5	0
39	20	6	290	20	6	47,100	80	100
40	20	3	50	10	5	25,320	11	0
41	21	6	350	22	9	82,100	85	100
42	21	9	510	23	7	62,900	15	0
43	21	19	1,111	40	13	159,245	95	100
44	21	8	291	26	8	71,887	15	0
45	21	5	240	17	6	87,700	95	50
46	21	3	302	13	2	67,232	1	50
47	22	7	310	18	7	62,190	94	100
48	22	5	44	18	4	35,560	15	0

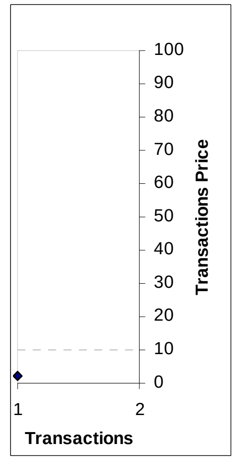
49	22	3	250	14	7	99,950	95	50
50	22	1	50	13	3	76,600	2	50
51	22	3	130	15	8	40,800	94	0
52	22	6	158	19	7	31,890	5	100
53	23	3	410	21	12	148,600	90	100
54	23	11	1,874	20	9	118,970	10	0
55	23	1	20	6	2	22,000	50	50
56	23	2	220	7	5	37,400	75	50
57	23	3	100	19	5	120,950	90	50
58	23	10	699	20	6	119,339	11	50
59	24	0		5	4	80,000		0
60	24	1	100	4	2	86,000	60	100
61	24	1	300	4	3	73,600	92	100
62	24	2	150	8	4	47,050	8	0
63	24	1	100	4	3	46,000	35	0
64	24	1	200	5	4	54,500	60	100
65	25	5	300	14	7	66,000	30	0
66	25	6	420	22	8	93,250	80	100
67	25	1	100	6	3	19,000	15	0
68	25	1	100	6	3	25,000	75	100
69	25	3	300	11	7	46,100	55	50
70	25	5	389	11	7	60,210	90	50
71	25	2	100	6	3	38,750	90	100
72	25	1	300	7	4	31,500	5	0
73	26	12	690	26	12	146,100	58	50
74	26	18	1,615	38	14	220,100	90	50
75	26	5	303	11	5	45,380	60	100

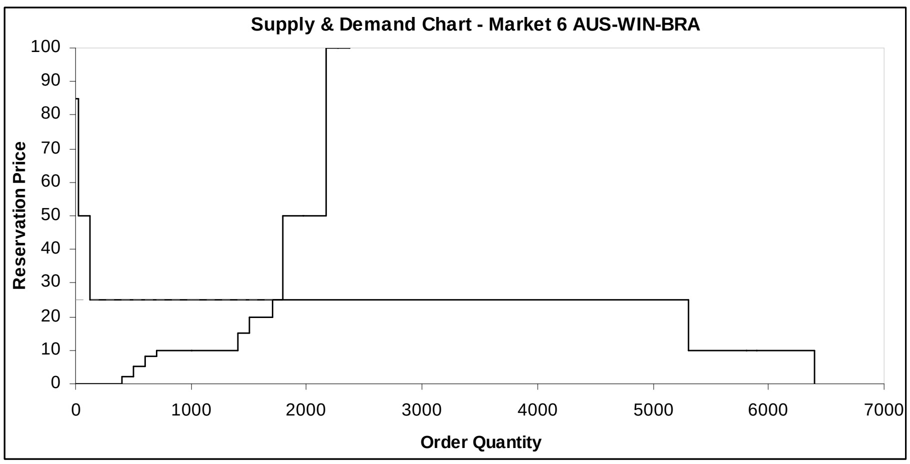
76	27	2	100	6	3	25,700	30	0
77	26	2	500	8	4	83,750	80	100
78	26	1	100	6	3	45,750	20	0
79	26	0		5	2	15,000		50
80	26	1	100	5	2	21,500	65	50
81	27	4	155	15	5	30,475	25	0
82	27	2	103	9	5	34,225	75	100
83	27	11	1,001	21	8	100,910	45	100
84	27	4	1,000	11	4	165,150	100	0
85	27	17	2,773	60	11	182,195	2	0
86	27	4	731	14	8	192,451	98	100
87	27	4	404	9	5	63,770	70	50
88	27	6	111	15	4	43,285	40	50
89	29	1	100	5	3	40,500	5	0
90	29	3	600	12	7	90,500	90	100
91	29	8	325	18	8	60,770	60	100
92	29	7	380	19	9	47,325	45	0
93	28	3	150	15	6	31,850	5	0
94	28	3	320	10	7	57,620	90	100
95	28	4	250	11	7	36,500	75	100
96	28	1	50	4	3	20,250	30	0
97	5	4	760	9	6	135,300	70	100
98	5	3	400	8	6	89,500	35	0
99	6	5	203	12	8	58,830	95	100
100	6	7	363	18	8	45,723	20	0
101	5	3	300	8	4	58,000	95	100
102	5	2	200	5	4	31,500	5	0

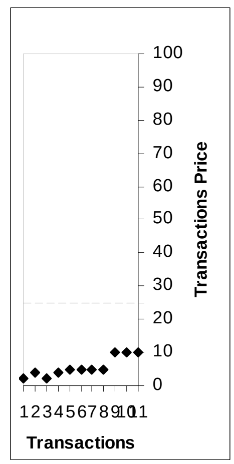
103	5	1	100	10	6	71,900	70	100
104	5	5	255	13	5	81,610	66	0
105	5	2	10	6	4	33,050	90	100
106	5	7	179	17	6	33,910	9	0
107	6	1	1	5	3	110,199	99	100
108	6	4	500	15	6	114,100	5	0
109	5	5	305	23	5	103,050	70	0
110	5	13	938	28	7	140,930	65	100
111	5	4	105	14	5	90,725	70	0
112	5	2	45	33	5	83,955	34	100
113	7	11	1,250	43	7	218,750	85	100
114	7	24	1,742	69	6	229,251	53	0
115	7	20	1,847	48	10	303,365	85	0
116	7	18	1,376	60	8	258,085	35	100
117	5	4	350	16	5	160,100	90	100
118	5	5	225	32	4	132,225	25	0
119	5	9	1,050	19	4	421,450	96	0
120	5	9	801	36	4	335,199	18	100
121	5	17	3,066	43	5	600,360	60	0
122	5	11	1,280	36	5	468,500	60	100
123	5	2	500	26	4	318,250	59	0
124	5	2	350	27	5	304,000	55	100
125	4	0	--	9	2	50,000	--	100
126	4	0	--	10	1	50,000	--	0
127	6	20	5,008	45	7	574,630	60	100
128	6	10	3,500	27	4	575,400	60	0

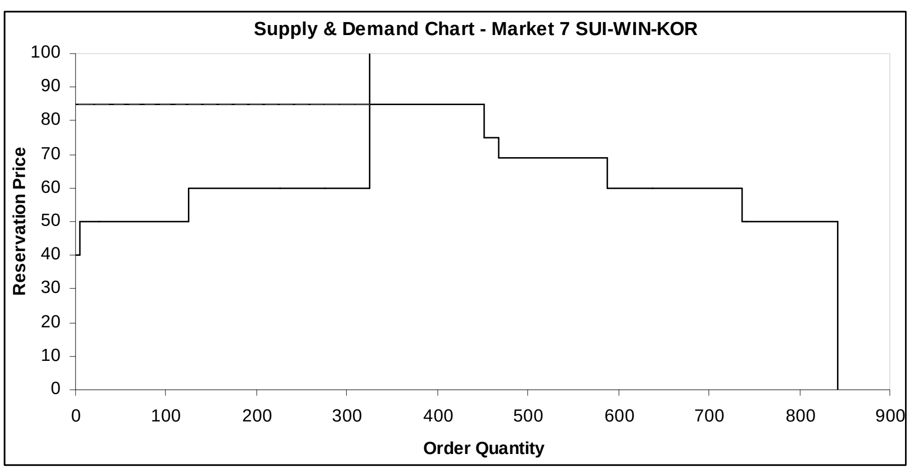
E.2 Supply and Demand Graphs of Selected Markets

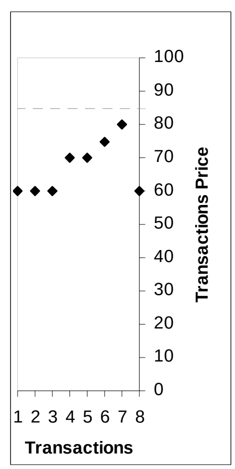

Supply & Demand Chart Market - 4 USA-WIN-ITA
Reservation Price
Order Quantity

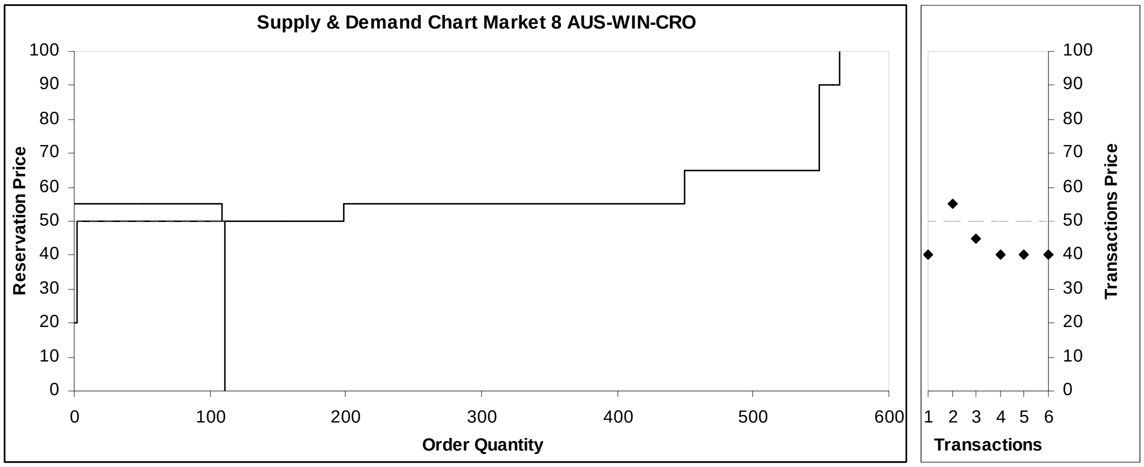

Transactions Price
Transactions

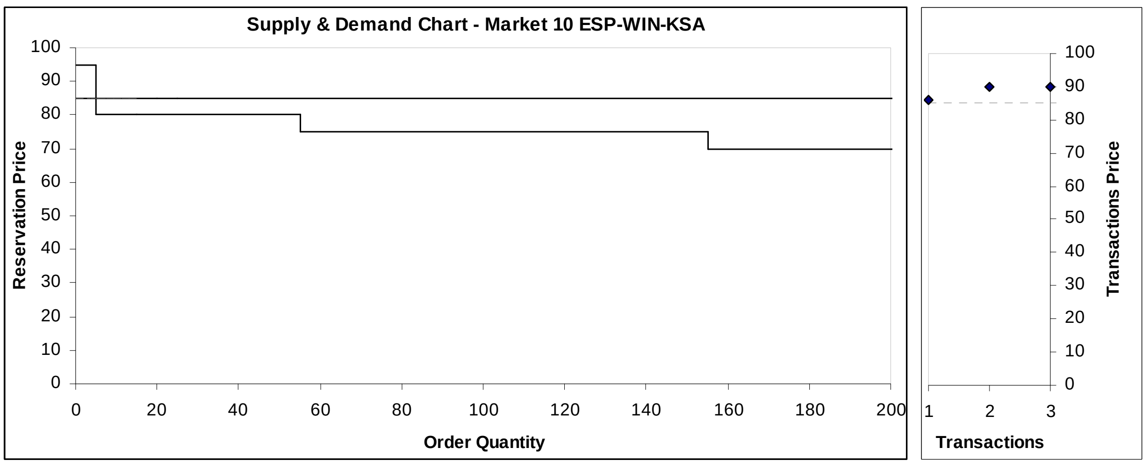

Supply & Demand Chart - Market 6 AUS-WIN-BRA
Reservation Price
Order Quantity

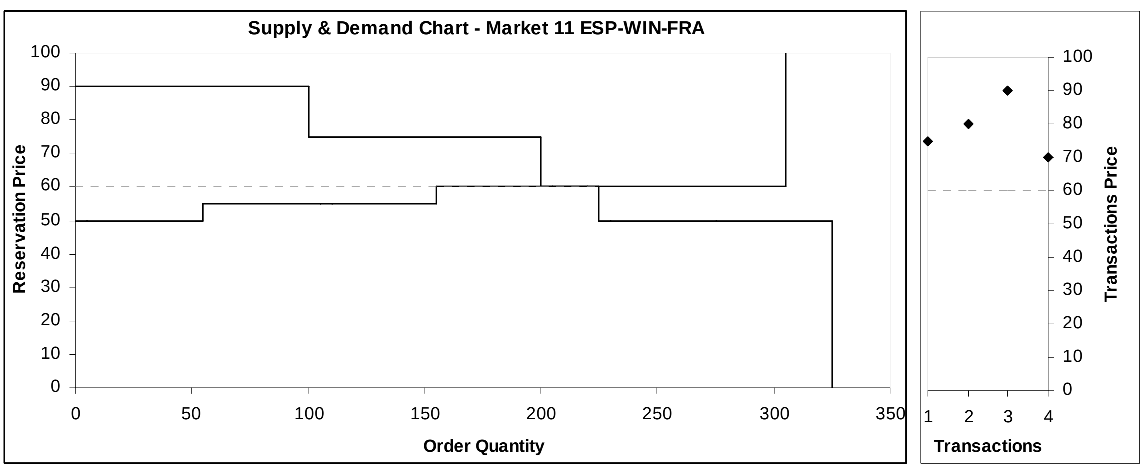

Transactions Price
Transactions

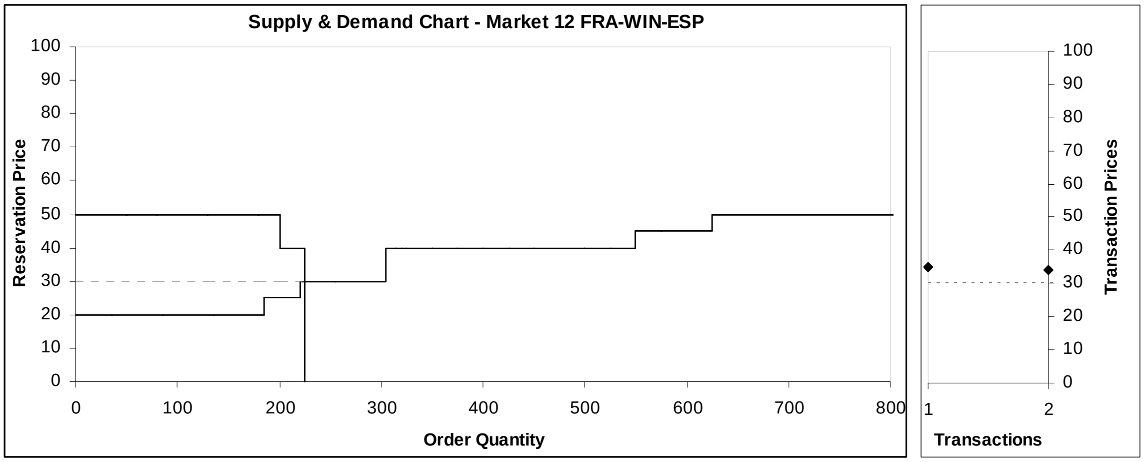

Supply & Demand Chart - Market 7 SUI-WIN-KOR
Reservation Price
Order Quantity

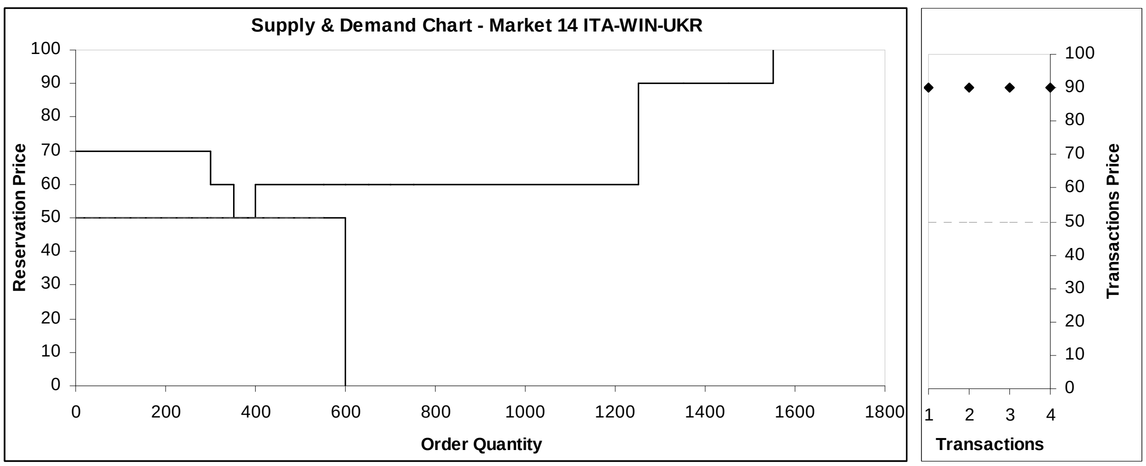

Transactions Price
Transactions


Supply & Demand Chart Market 8 AUS-WIN-CRO
Reservation Price
Order Quantity
Transactions Price
Transactions


Supply & Demand Chart - Market 10 ESP-WIN-KSA
Reservation Price
Order Quantity
Transactions Price
Transactions


Supply & Demand Chart - Market 11 ESP-WIN-FRA
Reservation Price
Order Quantity
Transactions Price
Transactions


Supply & Demand Chart - Market 12 FRA-WIN-ESP
Reservation Price
Order Quantity
0 100 200 300 400 500 600 700 800
0 10 20 30 40 50 60 70 80 90 100
Transaction Prices
Transactions
1 2


Supply & Demand Chart - Market 14 ITA-WIN-UKR
Reservation Price
Order Quantity
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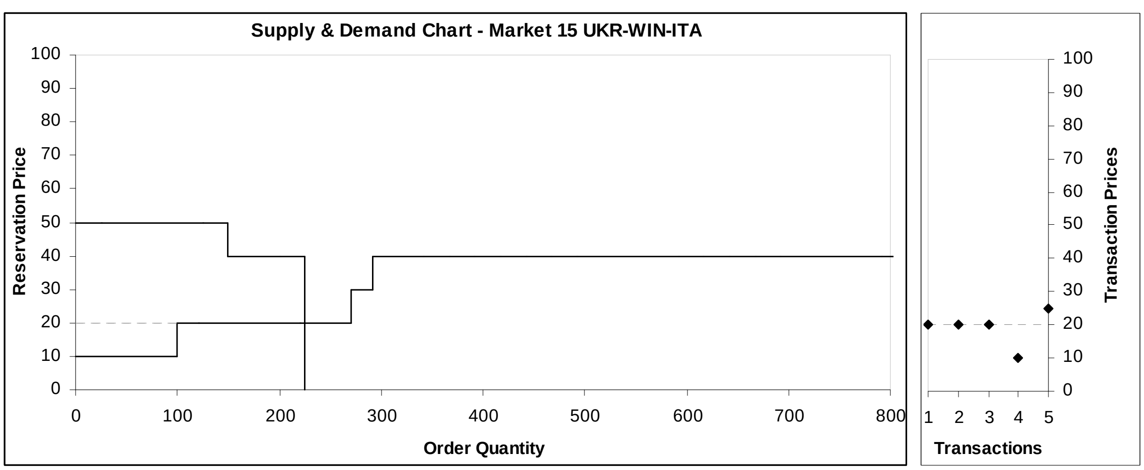
0 10 20 30 40 50 60 70 80 90 100
Transactions Price
Transactions
1 2 3 4


Supply & Demand Chart - Market 15 UKR-WIN-ITA
Reservation Price
Order Quantity
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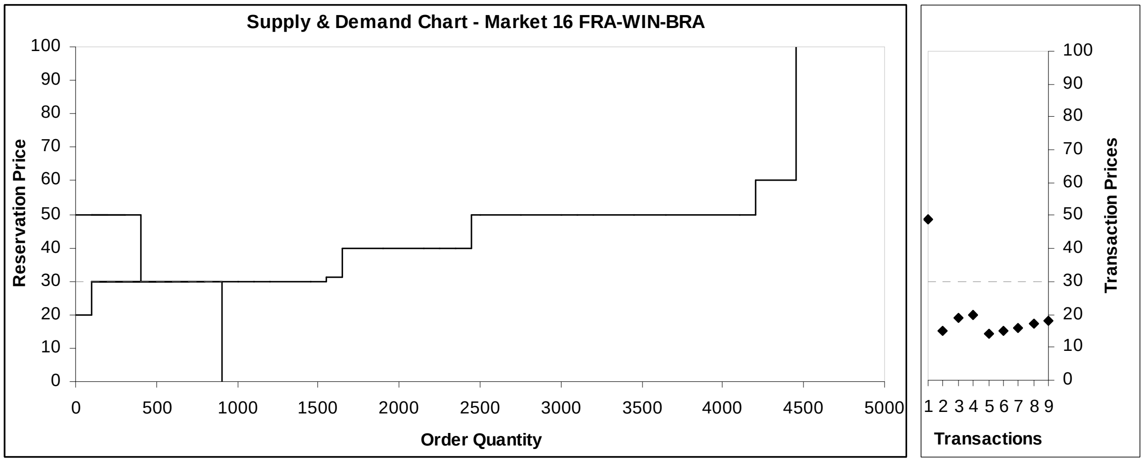
0 10 20 30 40 50 60 70 80 90 100
Transaction Prices
Transactions
1 2 3 4 5


Supply & Demand Chart - Market 16 FRA-WIN-BRA
Reservation Price
Order Quantity
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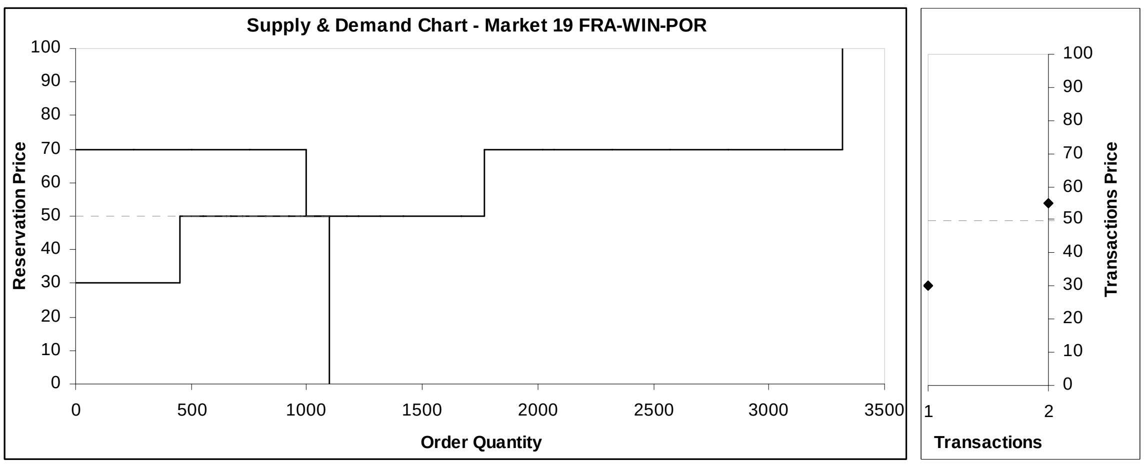
0 10 20 30 40 50 60 70 80 90 100
Transaction Prices
Transactions
1 2 3 4 5 6 7 8 9


Supply & Demand Chart - Market 19 FRA-WIN-POR
Reservation Price
Order Quantity
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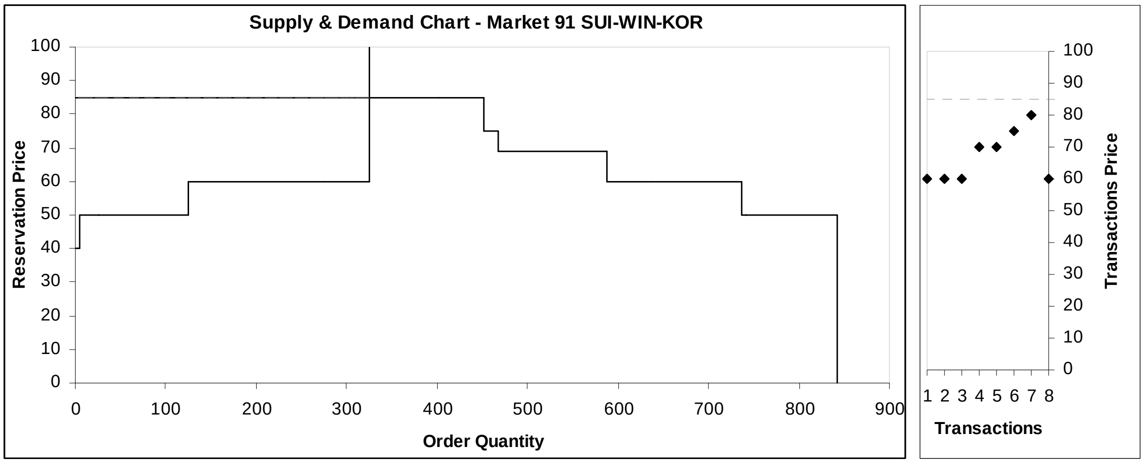
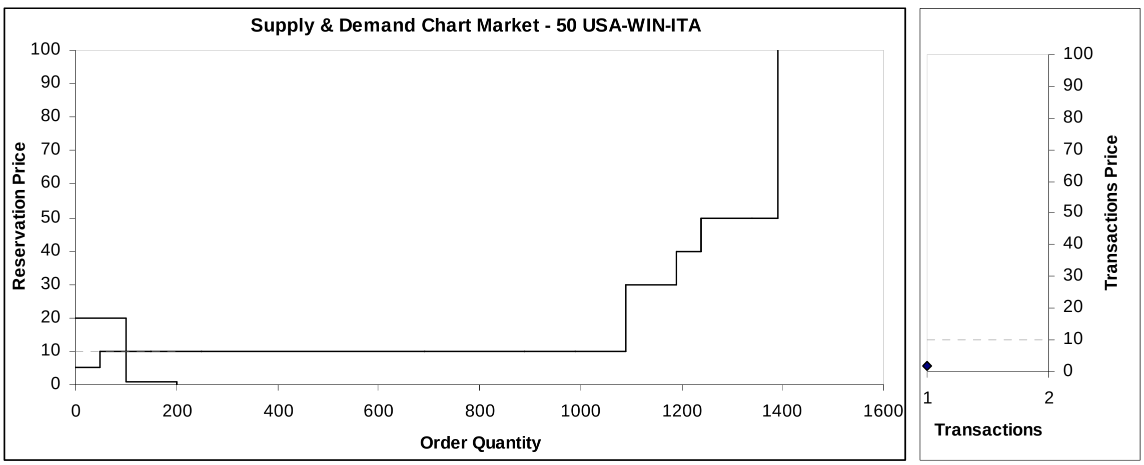
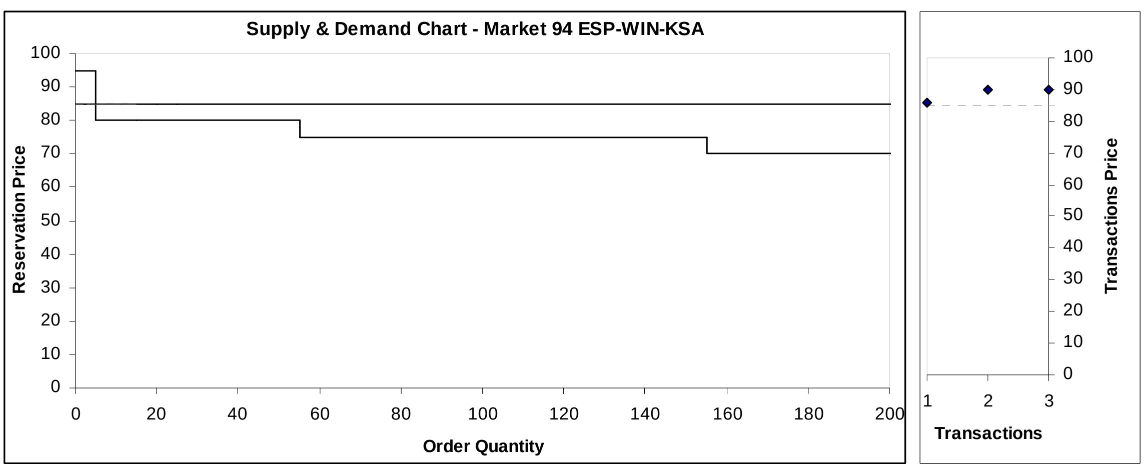
0 10 20 30 40 50 60 70 80 90 100
Transactions Price
Transactions
1 2


Supply & Demand Chart - Market 91 SUI-WIN-KOR
Reservation Price
Order Quantity
Transactions Price
Transactions


Supply & Demand Chart Market - 50 USA-WIN-ITA
Reservation Price
Order Quantity
Transactions Price
Transactions


Supply & Demand Chart - Market 94 ESP-WIN-KSA
Reservation Price
Order Quantity
Transactions Price
Transactions