SHENGYUN YANG

Information Aggregation Efficiency of Prediction Markets

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Informatie aggregatie efficiëntie van voorspellingsmarkten

Thesis

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To my beloved parents, Vic and friends

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Although I am now concluding my journey towards the PhD, this dissertation is just the beginning of my journey in the study of prediction markets. My passion for this research topic will go on.

Annie

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CHAPTER 1 INTRODUCTION

Forecasting is a fundamental activity of management within a company, because a forecast is often required when a decision is made (Armstrong 1985). Poor forecasting may lead to disastrous decisions and huge financial losses. Risk and uncertainty are central to forecasting. Nowadays, substantial changes to business and economic environments have increased risks and uncertainties for companies.

Within a company, a significant proportion of financial resources and managerial attention is now spent to develop and launch more and more new products every year, as new products can increase a company's long-term financial performance and market value (Ho and Chen 2007). Demand forecasts are critical to supply, production and launch date planning for each new product, and hence, the increased introduction of new products leads to more frequent forecasting. Poor demand forecasts prevent companies from capitalizing on the successes of a new product blockbuster, such as the huge shortage when the Nintendo Wii was launched and the delay of the international launch date of the iPod Mini (Ho and Chen 2007).

To seek and choose the most promising new product ideas in which to invest, companies have become increasingly proactive in sourcing ideas from front-line employees, managers and other personnel beyond the boundaries of research and development departments. Therefore, companies now seek agile and easily deployable means to collect and evaluate ideas for new products and services, addressing the challenges of intense and timely innovation (Botho et al. 2012). In other words, forecasting the success of a new product idea now requires more opinions from a wider variety of people.

Moreover, the globalization of markets brings higher complexity into forecasting. Companies need to know their home market but also understand unfamiliar overseas markets, including competitors, customer behavior, and culture. Particularly, the global market involves more complicated logistics management, and companies must be able to accurately forecast demand and to target resources (Page 2008).

Outside a company, financial crises, economic recessions, inflation, shortages, changes to commercial laws or treaties, and the occurrence of natural disasters all increase the uncertainty of management. Accordingly, these dynamic environments have added to the difficulty of forecasting (Zhang et al. 1998), though they have focused renewed attention on forecasting and the benefits it can provide (Makridakis and Wheelwright 1977).

Conventional forecasting methods become less accurate in the aforementioned environments. For instance, when a new product is launched statistical forecasting of demand has no sales data on which to base the demand estimate. Thus, statistical forecasting based on historical data does not perform as well for new products as it does for existing products (Berg et al. 2003b; Armstrong 2001). Likewise, target customers in a survey may not be able to give unbiased purchase intentions without learning from early adopters (Ho and Chen 2007), and opinion variance between experts is limited if they are few in number or if social pressure influences their appraisal (Hahn and Tetlock 2006; Ray 2006). Consequently, forecasts based on these methods are less accurate.

Over the past decade, some in the business world have come to believe that the best forecasts emerge from neither past behavior patterns nor far-removed experts who analyze markets (Malone 2004b). Rather, the best forecasts come from crowds; the front-line employees who are working directly with new products and services and interacting daily with buyers, sellers and customers in the field, as they have the most relevant and updated information and knowledge required for forecasting (Hahn and Tetlock 2006; Malone 2004b; Surowiecki 2004). The aggregation of information dispersed in groups is referred to as "the wisdom of crowds" (Surowiecki 2004) and companies are recommended to use it (also called "collective wisdom" or "collective intelligence") to make forecasts and decisions (Bonabeau 2009; Davenport and Harris 2009; Malone 2004a; Malone and Klein 2007; Malone et al. 2010; Surowiecki 2004).

1.1 INTRODUCTION OF PREDICTION MARKETS

A prediction market is an elegant and well-designed method for capturing collective wisdom and predicting the outcome of a future event (Surowiecki 2004). They can be powerful information-processing mechanisms that aggregate the views of multiple market traders to generate a prediction of the future (Kambil and Van Heck 2002). The use of prediction markets for aggregating information about the future is based on the efficient market hypothesis (e.g. Chen and Penncok 2010; Wolfers and Zitzewitz 2004), which asserts that financial markets are informationally efficient, and the rational expectations hypothesis (e.g. Berg et al. 2008; Bothos et al. 2012; Gruca et al. 2005; Hanson et al. 2006), which states that agents' expectations equal true statistical expected values. These theories suggest that prices in a market reflect all available information about the future, and therefore, prices imply the prediction of the future. Figure 1.1 illustrates how a prediction market works.

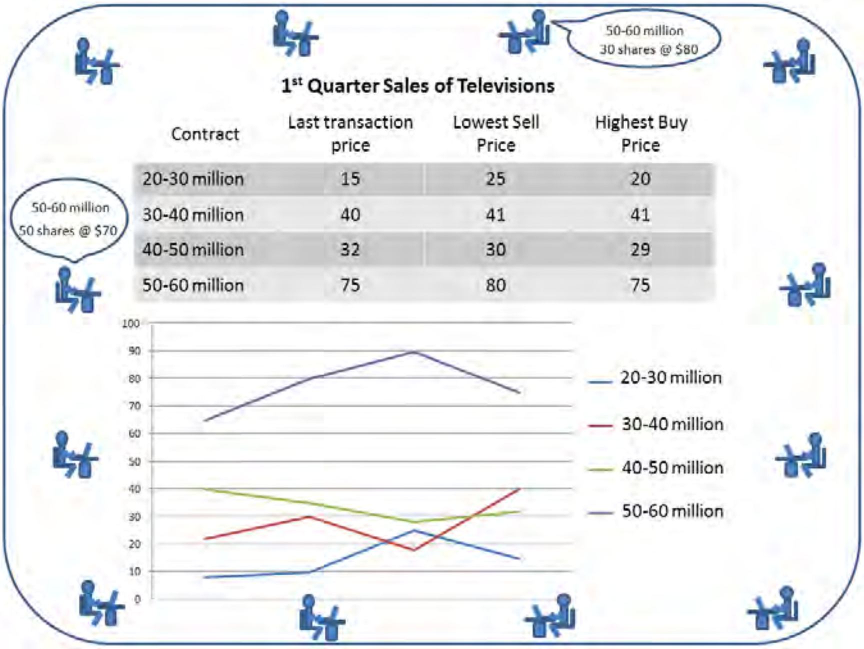

Figure 1.1 Illustration of How a Prediction Market Works

A prediction market works through a double auction mechanism, in which multiple traders are involved in trading contracts (Van Heck 2006). When a prediction market is used within a company, the traders are usually the employees of this company. The contracts represent the potential outcomes of a future event. As illustrated in Figure 1, the future event being predicted is a company's sales of televisions in the upcoming first quarter of a new year. Each contract represents a possible sales figure. For instance, contract "20-30 million" indicates that the sales of televisions in the first quarter will be between 20 and 30 million.

Traders reflect their opinions of the potential outcomes in the corresponding buying or selling prices. For instance, if a trader believes that sales in the first quarter are likely to be between 50 and 60 million, he or she will buy shares of the contract "50-60 million". Moreover, in order to be able to obtain this contract, he or she is willing to buy the shares of this contract with a higher buying price. On the contrary, if a trader thinks that sales in the first quarter are not likely to be between 50 and 60 million, he or she will sell the shares of this contract, and probably at a lower price in order to execute the sell order quickly.

The executed trades construct a market price for the contract. This price reflects the traders' consensus of the potential outcomes of the future event. For instance, as shown in Figure 1.1, the market price of the contract "50 and 60 million" is $75 (based on the last transaction price), implying the likelihood of the outcome presented by this contract is approximately 46%, the highest among all the contracts (the detailed measurement of the likelihood of a contract is discussed in Chapter 5.) This leading position indicates the traders' agreed opinion that sales of televisions in the upcoming first quarter are most likely to be between 50 and 60 million.

The pervasiveness of information technology (IT), particularly, the Internet, has enabled online prediction markets. Online prediction markets eliminate the temporal and spatial constraints of participation: traders all over the world can access a market, any time, anywhere. In turn, today's prediction markets are almost all online markets.

1.1 RESEARCH MOTIVATION

This dissertation entails five underlying motivations. First, prediction markets, in general, have inspired much enthusiasm among both researchers and practitioners in recent years by producing promising forecasting results. With regard to public prediction markets that are open to anyone (Cowgill et al. 2008; Nocera 2006), numerous markets can be listed (see Chapter 2). For example, in the earliest online prediction market, Iowa Electronic Market (IEM), 14 out of 15 markets concerning presidential elections in the United States predicted the winner accurately (Rhode and Strumpf 2004).

Internal prediction markets, used inside companies and only open to selected traders, who are usually employees (Hahn and Tetlock 2006; Plott and Chen 2002; Wolfers and Zitzewitz 2004), have shown similarly promising performance. For instance, Hewlett-Packard (HP) used prediction markets to forecast its sales. The markets beat official forecasts 75% of the time (Plott and Chen 2002; Spann and Skiera 2003); Eli Lilly adopted a prediction market to forecast the success of drugs. The market correctly forecasted the three most successful drugs (Hahn and Tetlock 2006; Pethokoukis 2004); and Intel used a prediction market to determine which factories should produce computer chips and when, which resulted in nearly 100% efficiency in allocating manufacturing capacity (Malone 2004b; Hopman 2007). More examples can be found in Chapter 2.

The second motivation is the complexity of prediction markets. Prediction markets embrace a number of noticeable advantages compared to other forecasting methods, including: (1)

motivation for traders to reveal their true opinions without deference to or influence by the majority (Ho and Chen 2007; Milgrom and Roberts 1992; Ray 2006); (2) incentives for traders to research and discover information (Bondarenko and Bossaerts 2000; Gruca et al. 2005; Malone 2004b; Rhode and Strumpf 2004); and (3) provision of an algorithm for aggregating opinions (Ho and Chen 2007; Ray 2006). Elaboration on the advantages of prediction markets can be seen in Chapter 2.

However, prediction markets as a forecasting method have disadvantages as well. The prediction market may not perform well under certain circumstances, such as little relevant or accurate information in the market (Malone 2004b; Wolfers and Zitzewitz 2004), little variance of information held by traders (Surowiecki 2004), or the possibility for traders to manipulate or distort the market for their own interest (Hanson et al. 2006; Sunstein 2006a). Elaboration on the disadvantages of prediction markets can be seen in Chapter 2.

Third, traders' behavior in a prediction market is dynamic and has a great effect on market performance. The number, composition, bias and manipulations of the traders in a prediction market all can have an impact on the outcome of the market (Berg et al. 2008; Hanson et al. 2006; Healy et al. 2010). Moreover, learning is the underlying activity of traders in a prediction market (Wolfers and Zitzewitz 2004). Traders keep learning from different information sources (Bondarenko and Bossaerts 2000; Gruca et al. 2005; Rhode and Strumpf 2004) and each other (Chen et al. 2009; Davis and Holt 1993). However, in a prediction market, not every trader is rational nor is every trader's rational level equal. Nevertheless, any trader can lead the market. While "marginal traders", who are more rational, can lead a market to efficiency (Forsythe et al. 1992), there have also been successful attempts to manipulate prices (Hansen et al. 2004; Hanson 2006). Thus, this dissertation will address the impact of the individual behavior of traders on the outcome of the market.

Fourth, while internal prediction markets have been identified as an exemplar of the future of work (Malone 2004b), the research on internal prediction markets is very limited compared to public prediction markets. Due to substantial differences between public and internal prediction markets, such as market focus, market size and market duration, (Cowgill et al. 2008; Plott and Chen 2002), the findings of the public markets probably cannot be applied in internal markets.

Furthermore, in the practice of management, many companies are grappling with incentives for traders and the potential ramification of prediction markets (Kiviat 2004). For instance, Plott, who ran the first HP prediction market, posed the contradiction between the real money and play money. Real money ensures that traders trade on their best information. However, companies that ask employees to risk their own money must face ethical questions. Eli Lilly did not have a strategy in place to handle conflict between the market forecast and the official forecast: should it follow the results from the market and assume the market is smarter? At Intel, there was concern that individual workers in a prediction market may face risks as well. Does it mean they are not knowledgeable about something they should be, if they lose money in the market?

Last, our research adopts the information-based view to study prediction markets, as information is the key in a prediction market. Traders in a market use and process different information in their personal estimation about a future event, reflected in their trading activities. Their trading activities in a market become a source of information for other traders; and the market aggregates the dispersed information from the traders through their trading activities. In turn, the fundamental element in a prediction market is information and the fundamental activity between traders is information exchange.

We particularly address information transparency in our research. Information transparency refers to the availability and accessibility of market information to its traders (Granados et al. 2010; Zhu 2004). Wolfers and Zitzewitz (2004) contended that the success of prediction markets, like any market, depends on their design and implementation. Information transparency is a fundamental issue in the design of markets (Bloomfield and O'Hara 1999). Bloomfield and O'Hara (1999) explicated that transparency, the real time, public dissemination of market information, plays a fundamental role in the fairness and efficiency of markets. Despite increased research attention (Bloomfield et al. 2009; Flood et al. 1999; Granados et al. 2006; 2007; 2008; Mollgaard and Overgaard 2000; Pagano and Röell 1996; Zhu 2002; 2004), there is little consensus as to the overall effects of information transparency on markets. Especially, due to the novelty of prediction markets, little research has studied the effect of information transparency on this new type of market. Consequently, our research concentrates on information transparency.

To summarize, the aforementioned disadvantages and potential problems of prediction markets raise many uncertainties and impede the further adoption of prediction markets, particularly inside a company; and information is fundamental throughout a prediction market. Therefore, this dissertation focuses on an information-based view of internal prediction markets.

1.2 RESEARCH OBJECTIVES AND QUESTIONS

This dissertation entails two major research objectives. First, we aim to understand traders' behavior in an internal prediction market. The aforementioned uncertainty of the human factor in a prediction market has been identified as a noticeable concern of companies (Kaviat 2004). Although traders' behavior is one of the major research streams of prediction markets, the study of traders in internal prediction markets is underdeveloped.

According to Cowgill et al. (2008), the characteristics of traders in public and internal prediction markets are different. In public markets, traders may not necessary have private information about the future event; while in internal prediction markets, as the participants are usually selected corporate employees, they have diverse specialized information about business events. Thus, traders in an internal prediction market are likely to be more informed than those in a public prediction market.

Besides, the behavior of traders in public and internal prediction markets is different. For instance, evidence drawn from the studies showed that traders in public prediction markets are likely to be less risk-neutral than traders in internal markets (Tetlock 2004; Cowgill et al. 2008). As less risk-neutral traders tend to show long-shot bias, the presence of long-shot bias is more likely to influence a public prediction market than an internal one (Ali 1977; Manski 2006).

Moreover, different conditions between public and internal prediction markets lead to different behavior among traders. For instance, the number of traders in an internal prediction market is far smaller than in a public prediction market. In turn, traders are able to and may manipulate or distort the market for their own interest in internal prediction markets (Hanson et al. 2006; Sunstein 2006a).

Therefore, it is important firstly to understand traders' behavior in an internal prediction market. Accordingly, the first major research question in this dissertation is as follows:

$\text{RQ}_{\text{main}}1$: *How do traders behave in an internal prediction market?*

The other fundamental objective of this dissertation is to investigate the effect of information transparency on prediction market performance. This research objective has two motivations. First, the effect of transparency on the market outcomes may differ in different types of markets (such as auctions and dealer markets) (Pagano and Röell 1996) and existing studies have revealed double-edged effects: the effect of information transparency is not always beneficial or equal to different stakeholders in a market. Therefore, no definitive answer to the effect of information transparency on market outcomes has emerged. Prediction markets, as a new type of market, however, have not been captured in existing research.

Second, Zhu (2002) contended that information transparency is one of the key features that distinguish digital exchanges from traditional markets. He argued that in a physical market, information is typically about past transactions or activities; in online markets, information is real time, more transparent and more synchronized. As contemporary prediction markets are all based on a digital platform, information transparency is definitely relevant to the study of prediction markets.

The second main research question is as follows:

$RQ_{main}2$: *How does information transparency in an internal prediction market influence market performance?*

1.3 RESEARCH METHODS

This dissertation adopts a pluralist methodology to validate the conceptual framework and investigate the research questions. Its major advantages are characterized by diversity and efficiency of study on the full richness and complexity of the real world, particularly within the context of information systems (IS) (Mingers 2001; Robey 1996).

Three different research methods based on the principles of discipline and engaged scholarship are used in this dissertation to triangulate the results. These three methods correspond to three empirical studies and are conducted in sequence. The results drawn from each study were used to plan the method of the following study.

First, we used case studies to explore traders' behavior in internal prediction markets, including their participation and interactions. We investigated the transaction data of two internal prediction markets in an international financial company to understand how actively employees participate and to what extent they interact with each other in a prediction market in the real business practice.

Second, we conducted laboratory experiments to examine the influence of information transparency in a prediction market on traders' behavior and market performance. We developed online prediction markets with "opaque" and "transparent" conditions and recruited university students as subjects for these experiments. To simulate the characteristics of internal prediction markets, we adopted the actual forecasting events and data of an e-commerce company.

Last, we conducted field experiments to investigate the impact of information transparency strategies on market performance. We developed online prediction markets with four different transparency levels and conducted the experiments in an e-commerce company in China. The traders were the employees of this company and the future events being predicted were actual management needs. These field experiments allowed us to investigate information transparency, traders' activities and market performance of internal prediction markets in a real business environment. The results of the field experiments enhance the validity of research on prediction markets used inside companies.

1.4 RESEARCH CONTRIBUTION

This dissertation contributes to the research on prediction markets and information transparency. First, this dissertation adds to the theory development of prediction markets by addressing information transparency. Existing studies on prediction market design focus on market mechanisms, contracts, traders and incentives. Our research is among the first to add information transparency as a factor in prediction market design. Therefore, our studies contribute to the research stream of prediction market design.

With regard to information transparency, as one of the first to theoretically develop and empirically test the impacts of information transparency in the context of prediction markets, this dissertation extends the previous studies on information transparency that focused only on business-to-business (Zhu 2004) or business-to-consumer markets (Granados et al. 2010). Unlike previous research, we examine not only the effect of opaque or transparent information conditions but also investigate different transparency levels. Thus, our dissertation advances the research in transparency strategy (Granados et al. 2010).

Furthermore, this dissertation defines the "information aggregation efficiency" of a prediction market, which had not been done before. We define the information aggregation efficiency of a prediction market as the ability of the market to synthesize the traders' mean belief. We also develop the measurement of information aggregation efficiency. Our definition and measurement distinguish the information aggregation efficiency and the predictive accuracy of a prediction market, which were confused and unidentified in previous studies.

Besides, this research focuses on internal prediction markets, and hence, adds to the literature on prediction markets used in companies and the business world. In particular, our research provides insights into traders' behavior, including traders' individual activities and interactions in internal prediction markets. Thus, we extend the research stream of traders' behavior in prediction markets.

Moreover, we contribute to the pluralist methodology by demonstrating the feasibility of using multi-method research in IS. Mingers (2001) argued that only a tiny proportion of IS empirical research has adopted multiple methods; the majority of these methods are in fact just a narrow spectrum centered around traditional approaches with very little by way of cross-paradigm linkages. This dissertation adopted different research methods, including case studies, laboratory experiments, field experiments and follow-up surveys. As a result, we extend the manifestation of a pluralist methodology in IS.

This dissertation further contributes to the managerial implications of empirical studies of internal prediction markets. First, empirical studies demonstrate the possibility of using prediction markets to gather dispersed information from employees and accurately forecast the future. Second, the research proposes general principles to guide organizations to design and operate an internal prediction market, particularly with regard to information transparency. Third, field experiments conducted in a new, dynamic and highly uncertain business environment demonstrate the considerable potential of prediction markets in managerial decision-making.

1.5 STRUCTURE OF THE DISSERTATION

This dissertation consists of seven chapters. Chapter 1 introduces the research topic and the overview of the dissertation. Chapter 2 reviews the literature on prediction markets and information transparency. Based on the literature review, we draw an overall conceptual framework. Chapter 3 justifies the overall research methodology and specific research methods. Subsequently, Chapters 4, 5 and 6 present the three empirical studies. Each study focuses on specific research questions. These studies together validate the overall conceptual framework. Finally, Chapter 7 concludes the key research findings drawn from the studies, elaborates the scientific, methodological, and managerial contributions of the dissertation, discusses the limitations of the research, and suggests future research.

CHAPTER 2 LITERATURE REVIEW

This chapter presents a survey of the literature on prediction markets, and focuses particularly on empirical studies of prediction markets. These empirical researches allow us to identify which areas have been investigated and what major findings have been revealed.

Based on the literature, we first identify the definition of prediction markets used in this dissertation. Second, we analyze the advantages and disadvantages of prediction markets compared to traditional forecasting methods. Third, we summarize the applications of prediction markets in the field and discuss the performance of these markets. Last, we classify the existing research into three main streams and discuss the major debates.

Moreover, we survey the literature on information transparency, which has been identified as an important and influential factor of markets (Bloomfield and O'Hara 1999; Granados et al. 2008). We summarize the effects of information transparency on markets drawn from the empirical evidence. Finally, we review the transparency strategies that have been identified and applied in markets.

2.1 INTRODUCTION OF PREDICTION MARKETS

Research on prediction markets is of interest to both academia and the business world. We, therefore, commence our literature review with a discussion of terminology and we present the definition used in this dissertation.

2.1.1 Terminology and Definition

The literature survey showed that different terms have been applied to "prediction markets". We identified eight commonly used terms. Table 2.1 lists these terms and examples of the corresponding references. We noticed that use of "prediction markets" is most common in the existing literature, accounting for approximately 50%. Recent literature, since 2007, has mostly adopted the term "prediction markets" (see Table 2.1). Accordingly, we use the term "prediction market" in this dissertation.

Similar to the terminology, there are various definitions of prediction markets. Table 2.2 shows some of these definitions. Essentially, there are two types of definitions. One describes the purpose of prediction markets; and the other describes the working mechanism and features of prediction markets. To explain the use of prediction markets and its fundamental working principle, we define prediction markets as follows:

Prediction markets are designed and conducted for the primary purpose of aggregating information so that market prices forecast future events. In such markets, a group of traders trade in contracts whose payoff depends on unknown future events.

2.1.2 Theoretical Foundation of Prediction Markets

Existing research has suggested that the use of prediction markets is based on two major theoretical foundations, the rational expectations hypothesis (e.g. Berg et al. 2008; Bothos et al. 2012; Gruca et al. 2005; Hanson et al. 2006) and the efficient market hypothesis (e.g. Chen and Penncok 2010; Wolfers and Zitzewitz 2004).

The rational expectations hypothesis states that, in the aggregate, the expected price is an unbiased predictor of the actual price (Muth 1961). According to this theory, all available information to traders in a market is revealed by prices in the process of trading (Grossman 1981; Lucas 1972; 1978).

According to the efficient market hypothesis, in an efficient market, prices always "fully reflect" all available information (Fama 1970). In a prediction market, traders trade contracts corresponding to a future event. In accordance with the efficient market hypothesis, in a truly efficient prediction market, contract prices reflect all available information about the future event. No combination of other information can be used to improve on the market-generated forecasts, and thus, the market price will be the best predictor of the event (Wolfers and Zitzewitz 2004).

The efficient market hypothesis and rational expectations hypothesis are neither contradictory nor mutually exclusive. The efficient market hypothesis is in fact the application of the theory of rational expectations to financial markets (Mishkin 2010). As the prediction market mechanism is similar to a financial market, the efficient market hypothesis is, therefore, identified as a theoretical foundation of prediction markets.

Hayek (1945) proposed the use of markets to aggregate dispersed information from market traders. He pointed out that the knowledge of the circumstances of which we must make use never exists in concentrated or integrated form. The knowledge exists solely as dispersed bits of incomplete and frequently contradictory information, possessed by the separate individuals.

Table 2.1 Terminologies of "Prediction Markets"

Terminologies	*References*
artificial markets	Pennock et al. (2000); Pennock et al. (2001a); Pennock et al. (2001b)
decision markets	Bean (2005); Hahn and Tetlock (2006); Hanson (1999)
electronic (stock) markets	Antweiler and Ross (1998); Brüggelambert and Crüger (2002); Forsythe et al. (1995); Forsythe et al. (1998); Forsythe et al. (1999); Gruca et al. (2003); Kou and Sobel (2004); Kuon (1991)
idea (preference) markets	Chen et al. (2009); Chen et al. (2010); Hanson (1992); Hanson (1995); Ottaviani (2009); Passmore et al. (2005); Spears et al. (2009)
information markets (information aggregation mechanism)	Chen and Plott (2002); Hall (2009); Hanson (2003); Tetlock (2004); Luckner and Weinhardt (2007)
political stock markets	Berlemann and Schmidt (2001); Bohm and Sonnegard (1999); Brüggelambert (2004); Forsythe et al. (1992); Forsythe et al. (1994); Hansen et al. (2004); Hauser and Huber (2005); Jacobsen et al. (2000); Ortner et al. (1995)
prediction (predictive) markets	Bell (2009); Berg et al. (2008); Berg and Proebsting (2009); Bergfjord (2008); Borghesi (2007; 2009a; 2009b); Christiansen (2007); Connor and Zhou (2008); Graefe and Weinhardt (2008); Gruca and Berg (2007); Gruca et al. (2008); Hall (2010); Healy et al. (2010); Kamp and Koen (2009); Lavoie (2009); Page (2008); Rajakovich and Vladimirov (2009); Reyes and Raifman (2008); Rhode (2009); Seemann et al. (2008; 2009); Siegel (2009); Slamka et al. (2008); Strumpf (2009); Wolfers and Zitzewitz (2004); Waitz and Mild (2009); Williams and Williams (2009); Wu et al. (2008)
virtual (stock) markets	Spann and Skiera (2003); Spann, et al. (2009); Foutz and Jank (2010)

Table 2.2 Definitions of "Prediction Markets"

Description Focus	*Definitions*	*References*
Purpose of Prediction Markets	Prediction markets are designed and conducted for the primary purpose of aggregating information so that market prices forecast future events.	Berg et al. (2003b, p. 3)
	Information Aggregation Mechanisms are economics mechanisms designed explicitly for the purpose of collecting and aggregating information.	Chen and Plott (2002, p. 1)
	An information markets is a self-organizing mechanism for aggregating information and making predictions.	Chen et al. (2005, p. 66)
	The goal of a prediction market is to aggregate relevant information from multiple and diverse people.	Ho and Chen (2007, p. 145)
	Prediction markets are designed to aggregate information and produce predictions about future events.	Servan-Schreiber et al. (2004, p. 243)
Working Mechanism and Features of Prediction Markets	Prediction markets, markets in which contracts are specifically designed so that prices forecast particular future events, appear poised for acceptance as alternatives to more conventional forecasting methods.	Berg and Rietz (2006, p. 142)
	Information markets are markets for contracts that yield payments based on the outcome of an uncertain future event.	Hahn and Litan (2006, p. xi)
	The basic concept [of a virtual stock market] involves bringing a group of traders together via the Internet and allowing them to trade shares of virtual stocks. These stocks represent a bet on the outcome of future market situations, and their value depends on the realization of these market situations.	Spann and Skiera (2003, p. 1310)
	[Prediction markets] are markets where traders trade in contracts whose payoff depends on unknown future events.	Wolfers and Zitzewitz (2004, p. 108)

As a result, the fundamental problem is the utilization of knowledge not given to anyone in its totality. He further suggested that this problem should be solved by some form of decentralization instead of centralization. To be specific, he explicated that the economic problem of society is mainly one of rapid adaptation to changes in the particular circumstances of time and place. Therefore, the problem should be solved by the people who know of the relevant changes and the resources immediately available to meet them. To communicate information, a mechanism must be adopted. Hayek (1945) proposed that the price system, which operates the economy of knowledge, can enable the individual participants to take the right action even with little knowledge, because the most essential information is passed on, and passed on only to those concerned, by price.

Hayek's (1945) proposal on the use of knowledge in society was in fact in line with the rational expectation theory and the efficient market theory. Malone (2004b) further contended that this decentralized form of decision-making is the future of work and a prediction market is an exemplar.

2.1.3 Prediction Markets vs. Traditional Forecasting Methods

Armstrong (2001) classified all the possible types of forecasting methods into two major categories, statistical and judgmental. Statistical methods make predictions by discovering a pattern of historical data. Judgmental methods make predictions by sourcing information from individuals. A prediction market is a judgmental method. Compared to other forecasting methods, a prediction market is novel. In turn, traditional forecasting methods, in this dissertation, refer to any other commonly used statistical or judgmental method.

2.1.3.1 Disadvantages of Traditional Forecasting Methods

Commonly used statistical forecasting techniques include time series models (e.g. historical values of the outcome to be forecasted with trends, auto-regressive and moving average components when needed) and structural models (e.g. regression models based on input variables estimated on past observations) (Berg et al. 2003b). Given a sufficient number of observations under essentially identical conditions and sufficient stationarity, statistical methods are more accurate than judgmental methods (Armstrong 2001; Berg et al. 2003b).

However, the events being predicted often lack sufficient data, stationarity or both (Berg et al. 2003b) and the environment is often too complex to model (Zhang et al. 1998). For instance, as companies increase the development of the extensions to existing products and new products and the business environment becomes increasingly dynamic, the availability of relevant historical data becomes constrained and the predictive power of historical data is reduced. In turn, judgmental methods have been increasingly adopted in the contemporary business environment.

Widely adopted judgmental forecasting methods include intentions (e.g. target customer survey about their purchase intentions) and expert opinions (e.g. pooling of experts' opinions) (Amstrong 2001). Both are deliberative associated methods, but with potential problems. For instance, as Ho and Chen (2007) argued, surveys do not motivate customers to reveal their true purchase intentions and do not provide customers with information that early adopters of new products have learned. Hence, the link between stated purchase intention and the ultimate purchase behavior is weak and customers give biased responses. They further pointed out that under the approach of pooling expert opinions, opinions are typically weighted equally, independent of the experts' knowledge. Moreover, experts' opinions may not be independent of each other because they rely on same information source. Consequently, the associated demand forecast is inaccurate.

2.1.3.2 Advantages of Prediction Markets

The advantages of prediction markets over the aforementioned traditional forecasting methods derive from the fact that they solve the problems of traditional methods. Wolfers and Zitzewitz (2004) summarized three major advantages of prediction markets.

First, prediction markets provide incentives for truthful revelation. In a prediction market, the trading process is usually anonymous. Particularly, in an Internet-based online prediction market, traders do not even see each other. Thus, whether traders know each other or not in their social networks, in a prediction market, they are not confronted with any social pressure, such as following group behavior (Hahn and Tetlock 2006; Ray 2006). Thus, prediction markets motivate traders to reveal their true opinions without deference to or influence by the majority (Ho and Chen 2007; Milgrom and Roberts 1992; Ray 2006). Moreover, since the reward (i.e. profit) and punishment (i.e. loss) are straight forward, the self-interest of profit in a prediction market motivates traders to reveal their private information (Ray 2006).

Second, prediction markets provide incentives for research and information discovery. Traders' self-interest in a prediction market is to profitably trade, and thus, they must improve their personal prediction accuracy. A common approach is to take into consideration more recent information. Bondarenko and Bossaerts (2000), Gruca et al. (2005), Malone (2004b) and Rhode and Strumpf (2004) demonstrated that traders keep updating their beliefs based on different information sources (e.g. news) available to them and reflect the updated information in their buy and sell orders. As a result, a prediction market encourages traders to explore and absorb additional accurate information so as to improve the accuracy or relevance of their personal information.

Third, the market provides an algorithm for aggregating opinions. It is reasonably assumed that some traders may have incentives to distort the information they provide so as to influence prices to their own benefits, leading to the exercise of monopoly. Nevertheless, because traders compete instead of collaborate in a prediction market, this monopoly power will be eliminated (Abramowicz 2006; Milgrom and Roberts 1992). As a result, traders who place a larger bet in a prediction market are likely to be more confident about their information. As Ray (2006) argued, by their structure, prediction markets automatically allow traders to bet as much money as they desire, using their specialized information in the hopes of profiting from it. This is how information will be given more weight in the aggregation process in a prediction market. The incentives derived from prediction markets in fact provide a natural way to weigh opinions (Ho and Chen 2007).

2.1.3.3 Disadvantages of Prediction Markets

Prediction markets, however, are unlikely to perform well under certain conditions. First, prediction market performance relies on relevant and dispersed information. If little relevant or accurate information exists in the market, the prediction market is not able to capture the entire picture of the future event (Malone 2004b; Wolfers and Zitzewitz 2004). Consequently, the prediction will not be accurate.

Second, traders are motivated by disagreement and contest rather than consensus or compromise (Surowiecki 2004). If traders hold similar information in a prediction market, they tend to carry homogeneous beliefs, leading to few trading activities. Consequently, information is not aggregated in the market.

Third, the weights that markets give to different opinions may not be an improvement on alternative algorithms where the accuracy of pundits is directly observable (Wolfers and Zitzewitz 2004). For instance, the public information on the probability of weapons of mass destruction in Iraq appears to have been of dubious quality, and hence, it is unsurprising that markets were as susceptible to be misled as general public opinion.

Furthermore, traders in a prediction market with a small group of traders have higher potential to manipulate or distort the market for their own interest. Manipulation and distortion undermine the capacity of the market for self-correction (Hanson et al. 2006) and hence, the collective result is not likely to be wise (Sunstein 2006a).

2.1.4 Field Applications of Prediction Markets

In this section, we first distinguish two types of prediction markets, public and internal. Second, we exhibit the examples of public and internal prediction markets. Thereafter, we discuss the performance of these prediction markets.

2.1.4.1 Public and Internal Prediction Markets

Prediction markets can be applied in public or private sectors and correspondingly categorized into public prediction markets or internal prediction markets (Hahn and Tetlock 2006). Public prediction markets give free entry to anyone (Cowgill et al. 2008; Nocera, 2006) while internal prediction markets are used inside companies and are only open to selected traders who are usually employees (Hahn and Tetlock 2006; Plott and Chen 2002; Wolfers and Zitzewitz 2004).

Internal prediction markets are substantially different from public prediction markets in various ways (see Table 2.3). For example, Plott and Chen (2002) noted that in public prediction markets, it is unclear if there is any specific or specialized information that is unavailable for the general public. As public reports of the event to be forecasted in a public prediction market are usually available, markets such as the Iowa Electronic Market (IEM), in fact are only effective and sophisticated systems of polling, collections of personal intentions, coordination mechanisms of public information, or combinations of polls. In other words, the information aggregated in public prediction markets is not necessarily inside information (beyond the personal intention to vote).

Furthermore, in internal prediction markets, traders are selected specifically from different parts of the business operation, as these traders are thought to have different inside information about the targeted events. This inside information (e.g. market intelligence, specific information about big clients and pricing strategies) must be aggregated. In addition, there are usually no public summaries of information available to the traders during the operation of the market.

Moreover, Cowgill et al. (2008) pointed out that public and internal prediction markets differ in market liquidity and traders' behavior as well. For instance, public prediction markets usually have a large number of traders, and thus do not have problems with liquidity. However, as internal prediction markets do not always have many traders, they are often confronted with limited trading. Additionally, evidence drawn from studies showed traders in public prediction markets are likely to be less risk-neutral than traders in internal markets (Tetlock 2004; Cowgill et al. 2008).

Table 2.3 Differences between Public and Internal Prediction Markets based on Plott and Chen (2002) and Cowgill et al. (2008)

Aspects	*Public Prediction Markets*	*Internal Prediction Markets*
Market focus	Public events (observable by public)	Corporate issues (partially observable by people who are close to the activity)
Traders	Every single individual	Selected corporate employees
Market size	Large	Small
Aggregated information	Personal intentions; public information	Different specialized information about business events
Market duration	Long	Short
Market liquidity	Likely to be high	Likely to be constrained
Traders behavior	Less risk-neutral	More risk-neutral

2.1.4.2 Applications in Practice

Public prediction markets appeared first in field applications. The IEM is perceived to be the first field application of prediction markets and is widely recognized (Berg and Rietz 2006; Ho and Chen 2007; Ray 2006). Operated by the University of Iowa Tippie College of Business, the IEM is a real-money prediction market, though not for profit. Although the first IEM prediction market in 1988 allowed only University of Iowa affiliates to participate, subsequent prediction markets have all been public and all the traders voluntarily invest between US$5 and US$500.

The IEM is best known for its United States and worldwide election markets. However, along with development and penetration, the IEM now has conducted markets on a broad range of events, such as political appointments, outcomes of legislative processes, international relationships, economic indicators, movie box office receipts, market capitalization after an initial public offering (IPO), corporate earnings forecasts, corporate stock price returns, and the incidence of influenza (Berg and Rietz 2006).

Another well-known but relatively new prediction market is the Hollywood Stock Exchange (HSX). The HSX allows people to use virtual currency to speculate on entertainment-related events, such as weekend and total box office returns on the upcoming movies, the success of the current season's new TV series, the impact of movie stars on movie's average gross, and the winners of Oscars (Ho and Chen 2007; Lamare 2007).

Besides, numerous public prediction markets have been established. Table 2.4a lists some of them that have been frequently discussed in the literature.

Nevertheless, the information of internal prediction markets is far more limited compared to public prediction markets. Table 2.4b shows some companies that have conducted internal prediction markets and reported the results, including the events being predicted.

Among these internal prediction market examples, the best-known is that of HP. In 1996, HP initiated its internal prediction markets. During three years, HP conducted 12 markets to forecast sales of various printer products. The traders were recruited from three HP divisions, including marketing, finance and HP labs. The duration of each market was always one week. However, the number of active traders and contracts varied in each market from 7 to 26 and from 8 to 10, respectively (Plott and Chen 2002).

2.1.4.3 Prediction Market Performance

Prediction market performance is commonly measured in two ways, accuracy and usability. Existing studies tend to measure accuracy rather than usability. Wolfers and Zitzewitz (2004) argued that the most important issue with prediction markets and the like is their performance as predictive tools. The accuracy of prediction markets can essentially be categorized in absolute terms against the actual outcome and in relative terms against predictions derived from competing forecasting methods (Berg and Rietz 2003). The smaller the discrepancy between a prediction and the actual outcome, the more accurate the prediction.

Table 2.4a Examples of Public Prediction Markets

Market	*Events being Predicted*	*Market Performance*	*Reference*
Economic Derivatives	Economic indices	The markets predicted as accurately as survey.	Gadanecz (2007)
Hollywood Stock Exchange (HSX)	Actual box office returns; Oscar award winners; and movie stars	The market always forecasted Oscar award winners correctly and its prediction of movie office-box revenues outperformed the expert judgments.	Wolfers and Zitzewitz (2004); Ho and Chen (2007); Lamare (2007)
Intrade	Politics; weather; technologies; entertainment; and finance.	Market prices correctly predicted the winner 36% of the time in the 2004 Democratic presidential nomination contest (compared to 13% for polls) and 54% of the time in the 2008 Democratic presidential nomination contest (compared to 45% for polls).	Cowgill, et al. (2008); Saxon (2010)
Iowa Electronic Market (IEM)	US presidential elections, US monetary policy; the severity of an outbreak in seasonal influenza; selected industry returns; and selected stock prices	The market was closer to the eventual outcome 74% of the time. Further, the market significantly outperformed the polls in every election when forecasting more than 100 days in advance.	Berg et al. (2008); Ray (2006); Rhode and Strumpf (2004); Wolfers and Zitzewitz (2004); Ho and Chen (2007)
NewsFutures	Political events; sport games; movies; global stock indices; and exchange rates.	The market predicted 66.8% favorite team victories (139 out of 208) and an average pre-game trading price of 65.6 for the favorite. The markets' trading prices accurately reflected actual frequency of victory.	Ray (2006); Servan-Schreiber et al. (2004); Wolfers and Zitzewitz (2004; 2006a)
TradeSports	Sport games; commodity prices; entertainment; exchange rates; and political events	65.9% favorite teams actually won their games (135 out of 208) and its average pregame trading price was 65.1 for the favorite, demonstrating the close correspondence between trading prices and the winning probabilities.	Ray (2006); Servan-Schreiber et al. (2004); Wolfers and Zitzewitz (2004; 2006b)

Table 2.4b Examples of Internal Prediction Markets

Company	*Market*	*Market Performance*	*Reference*
Eli Lilly	The success of drugs; the gain of approval from the Food and Drug Administration	Six markets predicted accurately against the actual outcomes.	Hahn and Tetlock (2006); Pethokoukis (2004)
Google	Demand, performance, company news, industry news, decision, and fun	270 markets revealed that market prices closely approximated event probabilities.	Cowgill, et al. (2008)
Hewlett Packard (HP)	Sales of information technology (IT) product	Six out of eight markets predicted more accurately than HP official forecasts.	Plott and Chen (2002); Ho and Chen (2007)
Intel Corporation	Manufacturing capacity	The markets produced forecasts at least the equal of the official figures and as much as 20% better (20% less error).	Malone (2004b); Hopman (2007)
Microsoft	Sales of software, bugs in the software, project management schedules	Highest price contract was usually the outcome of the event that happened.	Hahn and Tetlock (2006); O'Leary (2011)
Siemens	Software project completion	Markets correctly predicted that the firm would definitely fail to deliver on a software project on time, whereas the traditional planning tools suggested an opposite result.	Ortner (1998)

In general, prediction markets have proven to be uncannily accurate in predicting all types of events (Ray 2006). This contention can be supported by numerous evidences. Table 2.4a summarizes the accuracy of some well-known public prediction markets. For instance, in the earliest prediction market, IEM, 14 out of 15 markets concerning presidential elections in the United States predicted the winner accurately (Rhode and Strumpf 2004). In the HSX, prediction markets concerning Oscar award winners forecasted correctly eight out of eight times in 2005 and seven out of eight times in 2006 and 2007. Concerning movie office-box revenues, HSX achieved twice as many hits as the expert judgments (a 'hit' refers to a case where a specific forecasting instrument has the lowest absolute percentage error of all considered forecasting instruments for the same movie) (Lamare 2007; Spann and Skiera 2003).

Evidences drawn from internal prediction markets were limited compared to public prediction markets because fewer internal prediction markets carried out. Table 2.4b exhibits the accuracy of internal prediction markets. All these markets demonstrated that prediction markets not only predict accurately against the actual outcomes but also outperform competing forecasting mechanism. For example, in HP, six out of eight markets predicted more accurately than HP official forecasts (Chen and Plott 2002); Siemens' internal markets correctly predicted that the firm would definitely fail to deliver on a software project on time, whereas traditional planning tools suggested the opposite result (Ortner 1998); and the internal market prediction of the success of six Eli Lilly drugs was exactly the same as the actual outcome (Pethokoukis 2004).

The amazing forecasting accuracy of prediction markets may also be illustrated by an unexpected suspension of a market project. The United States Pentagon created the Terrorism Futures Market in 2003 in order to aggregate information regarding potential acts of terrorism, and in turn, the Pentagon would be able to preclude or at least hedge against such acts. However, the prices, which could inform the government about the terrorists' attack plans, could also inform terrorists about the government's security plans. Moreover, the terrorists might even have profited from inside information revealed in the market, which might have led to public outrage. Consequently, the market was terminated immediately after its inception (Hahn and Tetlock 2006; Ray 2006).

Usability, whether or not information can be used to make decisions, is another important measurement of market performance (Bocij et al. 2003). Wolfers and Zitzewitz (2006a) argued that prices provide useful estimates of average beliefs about the probability an event will occur, and hence, prediction markets ultimately can be used for decision-making (Ledyard 2006). This argument can be supported by the performance of internal prediction markets. For instance, the results based on 270 internal markets during two and half years in Google revealed that market prices closely approximated event probabilities (Cowgill et al. 2008).

In some cases, prediction markets may not outperform the competing mechanism in terms of accuracy, but they can provide additional information for decision-making. For instance, Gadanecz (2007) argued that "Economic Derivatives", in contrast to survey-based measures, produce true density forecasts, covering the whole distribution of the "market's view", not just point estimates. This information could be used to track the uncertainty of market traders about the state of the macroeconomy and to monitor the probabilities they attach to tail events. Chen et al. (2009; 2010) demonstrated that a Fortune 100 company used a prediction market for a first-stage screening process for emerging technologies. The company has decided to expand investment in the use of this prediction market.

2.2 MAJOR RESEARCH STREAMS OF PREDICTION MARKETS

Our literature survey suggested that the existing discussion of prediction markets concentrates on three areas. Most studies demonstrated the market's ability to accurately predict future events and aggregate information, addressing the aggregation level of a prediction market (see 2.2.1). Another stream of researches investigated traders' behavior in prediction markets, addressing the individual level of a prediction market (see 2.2.2). The third stream of literature focused on market design, identifying and discussing the important design aspects of a prediction market (see 2.2.3).

2.2.1 Accuracy and Information Aggregation

In this research stream, studies dealt with two aspects of prediction markets, prediction accuracy and information aggregation.

2.2.1.1 Accuracy

Noticeable evidences have manifested the powerful predictive ability of prediction markets, not only the point estimate (Gadanecz 2007) but also the probabilities (Wolfers and Zitzewitz 2006a). In section 2.4.1.3, we have illustrated the accuracy of prediction markets from field applications. Essentially, it is beyond doubt that prediction markets can make accurate forecasts.

Additional researches further investigated under which conditions a prediction market shows more or less powerful predictive ability. Two major results were drawn from the empirical studies. First, taking into consideration time horizons, prediction markets are viable forecasting tools both in the short run (e.g. forecasting one day or one week ahead) and in the long run (e.g. forecasting three months ahead). Their predictive accuracy outperforms competing methods (e.g. surveys) particularly in the long run (Berg et al. 2008). This result suggested that prediction markets are suitable when the events do not have a long history or a clear model for a statistical forecasting method.

Second, the predictive power of prediction markets reduces with the increased complexity of the environment. Healy et al. (2010) argued that prediction markets are likely to outperform in an environment a with relatively simple information structure (e.g. with one event and fewer contracts). In contrast, when the information structure becomes complex (e.g. with correlated multiple events and more contracts), other forecasting methods (e.g. Delphi) generate more accurate predictions. A possible reason is that traders tend to focus attention on a small subset of the possible outcomes of a future event, resulting in severe mispricing overall.

2.2.1.2 Information Aggregation

In prediction markets, some traders have a piece of information about the future event being predicted, but some do not (Plott 2000). The former are referred to as informed traders; and the latter are referred to as uninformed traders. However, markets are efficient, because information can be disseminated from the informed to the uninformed. This process is referred to as information aggregation (Gruca et al. 2005; Plott and Sunder 1982; 1988).

Information aggregation is processed through trading activities. A trader's individual bids and asks on a contract represent the value he or she expects of the contract. Similarly, a transaction on a contract represents the aggregate expected value of the contract. These orders and transactions in turn become public information available in the market and other traders learn from it. Gradually, with an increased number of trades, information about a future event is disseminated from the informed to the uninformed. In turn, traders' beliefs regarding the potential outcomes of a future event in a prediction market become convergent. Wolfers and Sitzewitz (2006a) and Gjerstad (2004) demonstrated that when the traders' beliefs are convergent, the market price in stock markets will be very close to the mean of market participants' beliefs. Accordingly, we define information aggregation efficiency as follows:

Information aggregation efficiency of a prediction market is the ability of the market to synthesize the traders' mean belief.

With regard to information aggregation, the central discussion point in the current literature is whether or not a prediction market can aggregate dispersed information from traders. The results showed positive findings. Gruca et al. (2005) asserted that prediction markets can aggregate private information held by traders and disseminate this information in the market by trading, and thus the market eventually aggregates the consensus of the traders. This result suggested that prediction markets facilitate decision-making by aggregating dispersed information.

Bothos et al. (2012) further exemplified the promising use of prediction markets in idea screening based on its information aggregating ability. They argued that prediction markets enable the acquisition of more ideas from individuals than forum-like idea suggestion systems, though the quality of ideas is similar between the two methods.

2.2.2 Traders' Behavior

The research in this area focused on the effect of uninformed traders and traders' manipulation of information aggregation and the predictive accuracy of prediction markets.

2.2.2.1 Presence of Uninformed Traders

Informed and uninformed traders are distinguished based on their possession of private information of future events. Informed traders are those who have some private information while uninformed traders do not (Berg et al. 2008). Empirical evidence has led to controversial discussions. Kyle (1985) argued that uninformed traders bring larger trades into the market and provide profit opportunities for informed traders, leading to the acquisition and integration of information. Berg et al. (2008) and Tetlock (2007) counter argued that although increased trading volume positively correlates to market predictive accuracy, the presence of uninformed traders leads to less accurate prediction and slower information convergence.

Experimental studies showed mixed results. Bloomfield et al. (2009) drew the conclusion that uninformed traders may increase trading volume but their trading diminishes the adjustment of market prices to new information, leading to lower informational efficiency. On the contrary, greater information aggregation was observed when uninformed traders were present (Healy et al. 2010), in line with Kyle's (1985) argument.

2.2.2.2 Bias and Manipulations

A trader's actions in a prediction market may be biased due to their opinions (e.g. wishful thinking) (Forsythe et al. 1992; 1999). Traders may also attempt to manipulate prices in order to gain in the market (Hanson et al. 2004). Related research showed that neither of these factors is able to distort prediction accuracy.

The fundamental argument was that the efficiency of the market does not depend on the average traders but on the so-called "marginal trader" (Forsythe et al. 1992). A marginal trader is relatively free of judgment bias, and thus consistently buys and sells at prices very close to the equilibrium price, which reflects all available information about future events (Forsythe et al. 1992). These traders are usually more rational and can drive the efficiency of market prices in spite of large numbers of traders who constantly display suboptimal behavior (Oliven and Rietz 2004).

Several reasons have been identified. First, biased traders may be driven from the market by losses incurred as a result of biased trading (Oliven and Rietz 2004). Second, biased traders may learn from market prices (Bondarenko and Bossaerts 2000; Gruca et al. 2005; Rhode and Strumpf 2004) and update their expectations in a way that defeats the bias (Oliven and Rietz 2004). Third, biased traders tend to be inactive (Forsythe et al. 1992). Highly biased traders generally tend to buy and hold contracts, leading to transitory effects on prices at most (Forsythe et al. 1992; 1999). Last, when setting at-market limit orders and setting prices, traders are much less mistake-prone. These traders, who "make" the market, are likely to be more rational (Forsythe et al. 1999). As a result, rational traders drive efficient markets.

With regard to manipulators, first, similar to biased traders, they face the risk of losses incurred as a result of "irrational" trading, and thus, may be driven from the market before their manipulations succeed. Second, manipulators attempt to make systematically higher price offers than other traders. However, the reluctance of non-manipulators to accept such high offers effectively cancels out the distortionary effects of manipulations (Hansen et al. 2004; Hanson 2006). Third, the increased profit opportunity from manipulators increases the effort by other traders to obtain relevant information, possibly increasing the price accuracy (Hanson 2006). Finally, when traders suspect the presence of manipulators and know in what directions manipulators would like to push the price, the manipulation becomes ineffective (Hanson et al. 2004; 2006). As a result, efforts to manipulate prices are unsuccessful (Camerer 1998; Rhode and Strumpf 2004).

Nevertheless, an exception was indeed found in empirical evidence. Hansen et al. (2004) reported successful attempts at manipulating prices in the IEM. Hanson (2006) argued that prediction markets are hard to manipulate, except for a thin market, where the number of traders is very limited, or during a short transition phase (Wolfers and Zitzewitz 2004).

2.2.3 Market Design

Existing studies on prediction market design focused on four key issues, including market mechanisms, contracts, traders and incentives.

2.2.3.1 Market Mechanisms

A prediction market mechanism determines how buyers and sellers are matched (Wolfers and Zitzewitz 2004). Wolfers and Zitzewitz (2004) identified four major mechanisms applied in prediction markets. First, the most-adopted prediction market mechanism is a continuous double auction (CDA), in which buyers submit bids and sellers submit asking prices and the mechanism executes a trade whenever the two sides of the market reach a mutually agreeable price. The second mechanism is a continuous double auction with a market maker (CDAwMM), who is willing to accept a large number of buy and sell orders at particular prices. The third mechanism is a pari-mutuel market (PM), in which all of the money that is bet goes into a common pot and is then divided among the winners. The last mechanism is market scoring rules (MSR), which can be thought of as sequential scoring rules with many traders.

Each mechanism has benefits and drawbacks. A CDA poses no risk for the market institution, as it only matches willing traders. However, a CDA may suffer from illiquidity in the form of huge bid-ask spreads or light trading (Hanson 2003; Pennock 2004). In turn, when the number of traders is small, a CDA may face a liquidity problem. A CDAwMM has built-in liquidity, as the market maker is usually affiliated with the market institution. Nevertheless, the market maker is exposed to significant risk of large losses. As a result, the liquidity comes at a cost. The advantage of both CDA and CDAwMM is their incentives for traders to continuously leverage information as soon as it becomes available. As a result, prices capture updated information exceptionally well (Pennock 2004).

A PM does not have the problem with liquidity or involve risks for loss, because traders can place a bet on any outcome at any time with no need of a market maker. Prices in this mechanism, however, do not reflect continuously updated information, as traders do not place bets until either all information is revealed or the market is about to close. Consequently, this market mechanism is not suitable for situations where information arrives over time (Pennock 2004). A dynamic pari-mutuel market (DPM), a hybrid between a CDA and a PM, was proposed by Pennock (2004) and solves the CDA problem of illiquidity and allows for continuous information incorporation, which is not possible in a standard PM. Nevertheless, this mechanism has the drawbacks of only one-sided liquidity of buy orders and unfixed payoff, which complicates a trader's problem of strategic optimization.

A MSR, developed based on scoring rules, can be conceptualized as a market that provides a two-sided automated market maker that is always willing to accept a trade on any event at some price. Therefore, it avoids the problem of illiquidity and allows for continuous information incorporation but implies risks (Hanson 2003; Pennock 2004). A MSR allows for simultaneous predictions over many combinations of outcomes instead of requiring separate markets for each combination of possible outcomes. Hence, the sum of traders' errors over all predictions is lower (Wolfers and Zitzewitz 2004).

2.2.3.2 Contracts

Contracts are tied to the outcomes of future events, and hence, contract design is pivotal to prediction markets (Wolfers and Zitzewitz 2004; 2006b). Three basic types of contracts in prediction markets have been distinguished (Wolfers and Zitzewitz 2004). The first type is "winner-takes-all" in which the contract costs some amount of money and pays off only if a specific event occurs. The price in a winner-takes-all market represents the market's expectation of the probability that an event will occur based on the assumption of neutral risk.

The second type of contract is "index", in which the amount that the contract pays varies in a continuous way based on a number that rises or falls. This contract price represents the mean value that the market assigns to the outcome.

The third type of contract is "spread", in which traders differentiate themselves by bidding on the cutoff that determines whether an event occurs. For example, in a game of football, either one team will win by at least a certain number of points or not. Combined with the setting that winners double their money while losers receive zero, the corresponding price indicates the market's expectation of the median outcome.

Clear, easily understood and easily adjudicated contracts are important for a prediction market to work well (Wolfers and Zitzewitz 2004; Ledyard 2006). The description of the contracts must be able to help traders distinguish the alternatives considered. However, a challenge can arise if the underlying facts tied to the contracts change unexpectedly. For instance, in Ortner's (1998) study, the internal prediction market on whether a software project would be delivered to the client on schedule was confronted with the change of the deadline extended by the client.

2.2.3.3 Traders

The discussion on traders in prediction markets concentrated on the number and the composition of traders. First, a large number of traders are thought to be necessary for the market to function well (Kambil and Van Heck 2002; Ho and Chen 2007). Since traders incorporate their information into their trading activities, more traders are likely to lead to more trading activities in a market, and thus more information will be aggregated in the market. In addition, Surowiecki (2004) and Abramowicz (2006) asserted that traders in a prediction market do not deliberate but compete. They argued that a larger number of traders may pose more intensive competition, and thus, motivate traders to actively trade on information available to them. Furthermore, a relatively large number of traders make it likely that there is accurate information of the future event in the prediction market (Sunstein 2006a).

With regard to the composition of traders, it has been argued that traders with different information in a prediction market are desirable. As mentioned above, traders in a prediction market are motivated by disagreement and contest rather than consensus or comprise (Surowiecki 2004; Abramowicz 2006). If they hold similar information, they tend to carry homogeneous beliefs, leading to few trading activities and impeding information aggregation. Therefore, a diversity of opinions of the future event should be considered in the prediction market design (Ray 2006).

It should be clarified that the number and the composition of traders are not mutually exclusive issues of prediction market design. A larger number of traders are, in fact, likely to have heterogeneous information.

2.2.3.4 Incentives

Incentives are given to motivate traders to trade and reveal information in prediction markets. The central research question of this design issue was how much difference it makes whether prediction markets run with real money or with play money (Wolfers and Zitzewitz 2004). Controversial results were drawn from the existing research. On the one hand, early studies revealed that prediction markets work better when "[the traders] put their money where their mouth is" (Hanson 1999). Since traders risk their own money, they tend to make better use of their information and proactively seek accurate information. In turn, the information aggregated in the market is more accurate.

On the other hand, Servan-Schreiber (2004) and Rosenbloom and Notz (2006) demonstrated that the predictions drawn from real-money markets and play-money markets did not differ significantly and both were accurate. Moreover, recent studies on play-money markets supported the conclusion that non-monetary incentives, as long as they were properly designed, were able to motivate traders to trade and reveal information in prediction markets (Chen et al. 2009; 2010; Cowgill et al. 2008).

Despite the aforementioned controversial discussion on real-money and play-money markets, it is beyond doubt that proper incentives can encourage participation and the revelation of information in prediction markets (Ledyard 2006).

2.3 INFORMATION TRANSPARENCY

Information transparency is defined as the degree of visibility and accessibility of information (Zhu 2002; 2004). In markets, information transparency is referred to as market transparency (Granados et al. 2006; 2007; 2008; Bloomfield and O'Hara 1999; Mollgaard and Overgaard 2000). Market transparency is defined as the level of availability and accessibility of information about products and market prices (Granados et al. 2008). The impact of information transparency on markets has raised enthusiasm for research on this topic.

2.3.1 IT Enabled Information Transparency in Markets

Research on information transparency is motivated by the development and use of information technology (IT). IT refers to technological artifacts that enable electronic markets, such as the Internet, network technologies and communication technologies (Granados et al. 2006). A common thread in the markets is that the Internet has caused a structural increase in the level of information transparency for two major reasons (Granados et al. 2008).

First, the electronic market hypothesis (EMH) posits that advanced IT reduces coordination costs between suppliers and buyers and motivates the dominance of electronic market-based forms of economic activity (Malone et al. 1987). The EMH predicts that biased electronic markets will emerge as suppliers take advantage of IT to lock in buyers. However, unbiased electronic markets will gradually dominate. In unbiased electronic markets, all products and suppliers can be evaluated by buyers to make well-informed decisions, and information is complete, accurate and real time (Granados et al. 2006; 2007; 2010). In this regard, information is more transparent in electronic markets than traditional physical markets (Zhu 2002).

Second, IT, such as the Internet, enables exchanges by providing an online platform in which a vast sea of information about products, prices, transactions and competitors is available. All the information is gathered, compiled, displayed and transmitted among traders. Zhu (2002) contended that the abundance of information that is available based on the Internet has, in general, made information more transparent in online markets.

2.3.2 The Double-Edged Effects of Information Transparency

Early studies on information transparency suggested the possibility that efficiencies would arise from more widespread dissemination of desired complete and accurate information (Kahn et al. 2002) and that all traders would prefer the full disclosure of private information, even to their rivals (Li 1985; Shapiro 1986). The "information transparency hypothesis", that open sharing of information in electronic markets is beneficial to all traders, has been thus introduced (Zhu 2002).

Recent research, however, has shown that previous studies on information transparency ignored many real situations, such as price competition, information confidentiality and information uncertainty, which may eventually influence the effect of information transparency on markets (Granados et al. 2008; Zhu 2004). In contrast to the previously held consensus about the benefits of information transparency, these studies have challenged the "information transparency hypothesis" and demonstrated that transparent information is in fact a double-edged sword. In other words, information transparency sometimes has a negative effect.

To be specific, Granados et al. (2008; 2010) revealed different effects of information transparency on different market positions (i.e. buyers, suppliers, and intermediaries) in a business-to-consumer (B2C) market. They argued that increased information transparency generally benefits consumers because they are able to better discern the product that best fits their needs at a better price. Granados et al. (2006) identified that information transparency benefits buyers in three ways. First, search costs decrease as more information is made available at no additional cost (Zhu 2002). Second, the value of a purchase increases if the buyer discerns product characteristics of existing alternatives with higher precision, resulting in more accurate product valuation (Hasbrouck 1995). Third, information may become available that allows a buyer to transact at a lower price for a given product (Stigler 1961). Suppliers and intermediaries, however, are commonly confronted with the trade-off between the benefits of a more transparent market to attract buyers and the risk of reduced profit due to better informed buyers and competitors (Porter 2001; Soh et al. 2006).

Even within the same market position (e.g. buyers or suppliers), a transparent market does not necessarily bring all traders the same effect. Zhu (2002) studied the traders' incentives to join an electronic market in the business-to-consumer (B2B) context and found that information transparency benefits some traders in a market but hurts others. In an online B2B market, suppliers can see the rivals' cost, as cost prices are disclosed. By making cost information transparent, suppliers with different costs would react accordingly. The low-cost suppliers will find it optimal to join the exchange due to their competitive price. On the contrary, high-cost suppliers will stay away from the exchange, as cost transparency exposes their uncompetitive costs in the market. From the buyers' side, as their willingness-to-pay is transparent, those with high willingness-to-pay will have stronger incentives to join the exchange than those with low willingness-to-pay. As a result, low cost suppliers and high willingness-to-pay buyers have strong incentives to join the online B2B market.

2.3.3 Transparency Strategy

IT not only increases the potential for complete, accurate, real time and unbiased market information but also the potential for concealment or information distortion (Granados 2006). Moreover, as information transparency brings different effects on markets, with respect to market design, information can be strategically revealed, concealed, biased and distorted, depending on the goals and market position of the information source (e.g. suppliers versus buyers) (Granados et al. 2010). For instance, sellers may take advantage of IT to present incomplete or distorted information. Under this circumstance, buyers cannot fully evaluate the product and make well-informed decisions. Thus, the sellers may lock in buyers at prices that favor the seller (Granados et al. 2006).

Granados et al. (2010) argued that information transparency, unlike information availability or information sharing, implies the intention to disclose or withhold information. Tapscott and Ticoll (2003) contended that information transparency is increasingly viewed strategically as firms consider the trade-off between attracting new customers with market information and the risk of losing information advantages to customers and competitors. Transparency strategy is therefore proposed, which is defined as the set of policies and decisions that a firm makes to disclose, conceal, bias or distort market information (Granados et al. 2010).

Based on existing literature, Granados et al. (2010) identified seven key components of transparency strategy, including the following: (1) information from (whom), the party considers the disclosure of information; (2) information to (whom), the party receives the information; (3) information elements, the categories of information, such as price (Granados et al. 2006; Soh et al. 2006), product (Bakos 1997; Mollgaard and Overgaard 2000), inventory

(Lyons 1996; Jain and Moinzadeh 2005; Dewan et al. 2007), cost (Sinha 2000; Gal-Or 1988; Zhu 2004), and process (Adomavicius et al. 2006); (4) potential actions, the possible actions with respect to the strategic revelation of the information, such as transparent, distorted, biased and opaque (Granados et al. 2006); (5) systems and mechanism design, the direct implications for IT and system design in accordance with the strategic decisions to reveal or conceal information; (6) transparency regime, the aggregate information disclosed by competitors, suppliers, buyers and customers, and other third parties; and (7) complementary strategies, the alignment and coordination with other related managerial decisions (Ellison and Ellison 2009; Granados et al. 2008).

The literature on transparency strategy is scarce and scattered across disciplines, as the Internet was not well-developed until the end of the last millennium (Granados et al. 2010). Existing studies on transparency strategy can be classified into three major research areas. The first research category addresses B2B transparency strategy and the disclosure of information from sellers to other firms in the supply chain. Related research revealed that information disclosure in B2B markets is an enabler of efficiency for supply chains and a strategic dimension for individual firms (Patnayakuni et al. 2006; Hoffman et al. 2002; Kim et al. 2005; Jain and Moinzadeh 2005). In turn, firms participate in transparent Internet-based channels as long as the efficiency in the supply chain is enhanced. However, even in these efficiency-seeking partnerships, traders may use information strategically, and it may not be in their best interest to be transparent (e.g. due to information confidentiality) (Corbett 2001; Kalvenes and Basu 2006; Zhu 2004). In this case, firms will stay away from transparent environments.

The second research area addressed information transparency and electronic market design. These studies identified transparency design features, which are related to information disclosure policies throughout the trading process (Granados et al. 2010). Online travel agencies (OTA), such as Hotwire and Orbitz (Granados et al. 2006, 2007), and other online markets (Soh et al. 2006; Smith 2002) were the primary objects of these empirical studies. The results drawn from the research showed that consumers demand both product and price information from different suppliers, so a common strategy for online markets is to be unbiased in the inclusion and display of information about supplier offerings (Granados et al. 2010). However, some OTAs biased markets by failing to equitably include product and price information from all sellers (Granados et al. 2006), to favor suppliers with whom they develop special arrangements (Granados et al. 2010; Soh et al. 2006; Smith 2002). Moreover, Viswanathan et al. (2007) found that consumers with transparent product information pay higher prices for a product than those with transparent price information. This reminds online intermediaries to carefully consider the conflicting interests of buyers and sellers with regard to price transparency and the need to satisfy both buyers and sellers.

The third category of research focused on transparency regimes and their impacts on competition, consumer welfare and market efficiency. In general, the related research aimed to determine the impact of higher transparency of competitive offerings on competition and concentrates on price and product transparency (Granados et al. 2010). Research findings suggested that the impact of price transparency is different according to product type. The effect of price transparency on price competition of homogeneous products is salient and will result in lower net prices. Even though suppliers form a tacit collusion, consumers are only partially offset, as they are better informed about the prices (Boone and Pottersz 2006; Campbell et al. 2005; Schultz 2005). On the other hand, price transparency makes collusion relatively more difficult for differentiated products, exacerbating price competition (Anderson and Renault 1999; Bakos 1997; Schultz 2004). With regard to product transparency, Bakos (1997) and Boone and Pottersz (2006) demonstrated that higher product transparency of differentiated products will likely lead to higher demand from consumers and higher prices. For homogeneous products, nevertheless, product transparency does not have an impact on consumers' purchase decisions.

2.4 SUMMARY

An increasing body of literature has appeared since the first field application of prediction markets, IEM. However, the literature survey revealed that research on prediction markets, particularly internal markets used in companies, is limited and the empirical evidence is constrained. The common threads of the existing studies are the description of prediction markets and demonstration of the market predictive power. Recent studies tended to investigate traders' behavior and market design. Moreover, increased literature on IT-enabled information transparency in markets has motivated empirical studies in various online markets (e.g. B2B and B2C). However, prediction markets have not been addressed.

The aforementioned findings imply that further empirical studies could investigate prediction market design from the perspective of information transparency, particularly, in the context of internal prediction markets. The analyses ought to include the individual level (i.e. traders' behavior) and the aggregation level (i.e. market performance). Theorizing based on related empirical research is also necessary. All these are attempted in this dissertation as illustrated by the conceptual framework (see Figure 2-1). As the conceptual framework research model shows, this dissertation investigates the effect of information transparency on prediction market performance through traders' individual behavior. We particularly focus on traders' activity and the interactions of traders' behavior and market predictions and the information aggregation of market performance. The detailed construction of hypotheses together with the related theories are further elaborated in the following chapters on the case study, the laboratory experiment and the field experiments (see Chapter 5 and 6).

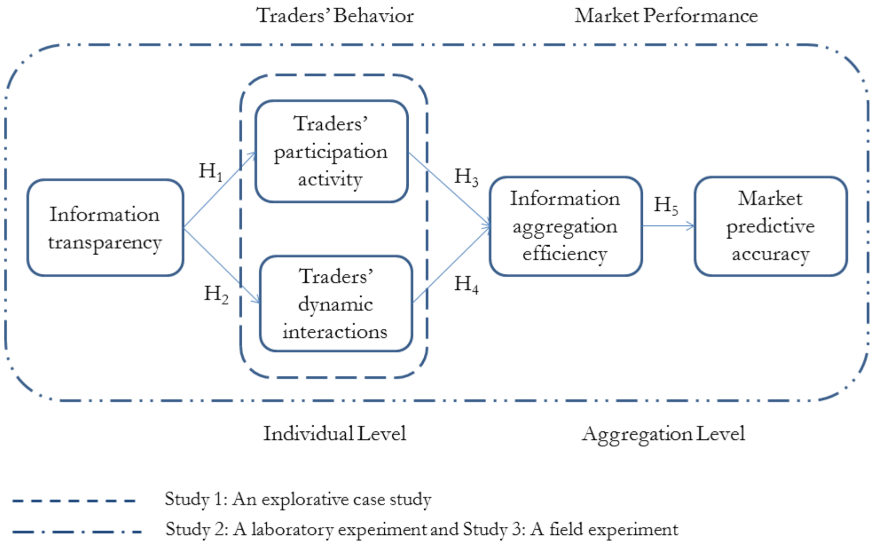

Figure 2.1 Conceptual Framework of the Dissertation

CHAPTER 3 RESEARCH METHODOLOGY

This chapter discusses the research methodology applied in this dissertation. To validate the conceptual model and answer the research questions, this dissertation adopted a pluralist methodology (Mingers 2001). The plan of this chapter is as follows. We first justify the use of a pluralist methodology in IS. Subsequently, we discuss the rationale of the chosen methodology based on the principles of discipline and engaged scholarship. Guided by the aforementioned rationales, we present our overall method, namely triangulation, and justify the use of specific research methods, including explorative case studies, laboratory experiments and field experiments.

3.1 RATIONALE OF PLURALIST METHODOLOGY IN IS

Methodological pluralism refers to a position that favors a diversity of methods, theories, even philosophies, in scientific inquiry (Landry and Banville 1992). It lies between the extremes of methodological monism and the anarchy of an "anything goes" attitude (Landry and Banville 1992; Robey 1996). Landry and Banville (1992) argued that methodological pluralism in IS emerged because of the gradual unfolding of the human, organizational and social dimensions of this discipline.

Robey (1996) identified four major advantages of the pluralist methodology characterized by diversity particularly within the context of IS. The pluralist methodology: (1) expands the foundation upon which knowledge claims in the field are based; (2) attracts good people to the field of IS where they can address applied problems that interest them; (3) fosters creativity; and (4) advances the valued principle of academic freedom.

Specifically, with regard to research methods, Mingers (2001) and Robey (1996) contended that multimethod research is desirable for IS to effectively study the full richness of the real world. The real world is characterized by complexity: an event consists of a multifaceted structure. Different research methods focus on different aspects of reality and therefore a richer and more reliable understanding of the research topic will be gained by combining several methods together in a single piece of research or a research program (Mingers 2001).

Moreover, each research method has its strengths and weaknesses. Therefore, the adoption of multiple research methods compensates for deficiencies in other methods. For instance, field studies allow researchers to gain insights into a phenomenon within its context and reveal important variables and their possible relationships (Eisenhardt 1989; Eisenhardt and

Graebner 2007; Pettigrew 1990; Yin 2003). However, the high generalizability of field studies comes at the cost of internal validity (Scandura and Williams 2000). By contrast, laboratory experiments achieve higher internal validity because they are executed in a controlled environment (Shadish et al. 2002). Nonetheless, the generalizability of laboratory experiments is low. To increase internal and external validity, the use of multimethod research is desired.

3.2 RATIONALE OF RESEARCH METHOD CHOICE

The appropriateness of a research method differs for each research situation. Therefore, a choice and design of research methods should be made based on the premise of the study (Landry and Banville 1992). Landry and Banville (1992) suggested a more disciplined approach to the selection of research methods drawn upon Laudan's (1984) triadic network of justification.

Landry and Banville (1992) suggested a disciplined approach and asserted that the choice of a specific research method in IS should be justified on pragmatic grounds as appropriate tools for accomplishing research aims. They cautioned against conforming to a dominant paradigm or the researcher's belief in its intrinsic value (Robey 1996). In other words, researchers must have clearly defined research aims that justify their choices of particular methods.

Furthermore, regarding how to decide which research aims to pursue, Robey (1996) pointed out that researchers, not only in IS but also in other fields, usually pursue aims of interest only to themselves. In fact, a more justifiable criterion of selecting research aims is to relate aims to practical interests in the IS field (Robey 1996). This argumentation is consistent with Van de Ven's (2007) emphasis on engaged scholarship.

Van de Ven (2007) argued that engaged scholarship implies a fundamental shift in how scholars define their relationships with communities. He defined this engagement as a relationship that involves negotiation and collaboration between researchers and practitioners in a learning community: such a community jointly produces knowledge that can both advance the scientific enterprise and enlighten a community of practitioners. He proposed that this approach of engaged scholarship can address the widening gap between research and practice in management.

3.3 TRIANGULATION AND SPECIFIC METHODS

Triangulation is a form of the pluralist methodology. Denzin (1978) defined triangulation as the combination of methodologies in the study of the same phenomenon. Denzin (1978) drew a distinction between within-method and between-method triangulation. Within-method triangulation refers to the use of multiple techniques within a given method to collect and interpret data, such as a survey questionnaire with different scales measuring the same "empirical uniP3". Between-method triangulation refers to the use of multiple methods to examine the same dimension of a research problem.

Jick (1979) concluded that within-method triangulation essentially involves cross-checking for internal consistency or reliability while between-method triangulation tests the degree of external validity. He asserted that the latter type represents the most popular use of triangulation, because it is largely a vehicle for cross validation when two or more distinct methods are found to be congruent and yield comparable data. In this dissertation, we adopt a between-method triangulation, involving case studies, laboratory experiments and field experiments.

Between-method triangulation can be further classified into simultaneous (or parallel) and sequential triangulation (Brewer and Hunter 1989; Mingers 2001). Simultaneous triangulation refers to the use of multiple methods in the same study to measure the same phenomenon. By checking the consistency of multiple evidences, the results of the study are considered more convincing. For instance, a questionnaire survey and interviews are conducted independently to collect data for the same phenomenon, and then their results are compared to reveal consistency or inconsistency. Sequential triangulation requires a researcher to use the results of one method as the basis for a new study of the same concept with a different method. In turn, the methods are dependent. For instance, a statistically analyzed questionnaire is done first, followed by in-depth interviews to better understand the results (Mingers 2001).

We use sequential triangulation in this dissertation. Each study adopts a specific method and the results drawn from it are used to plan the method of the following study. We justify the choice of research method in each study as follows.

3.3.1 Study 1 – Explorative Case Studies

A case study is an empirical inquiry that investigates a contemporary phenomenon within its real-life context, especially when the boundaries between a phenomenon and context are not clearly evident (Yin 2003). Yin (2003) identified three fundamental conditions of research to determine the appropriate use of case studies, including the following: (1) the type of research question posed; (2) the extent of control an investigator has over actual behavioral events; and (3) the degree of focus on contemporary as opposed to historical events. A case study is most appropriate method when (1) a research question focuses on how or why, (2) an investigator does not require any control over actual behavioral events, and (3) the research examines contemporary events and the relevant behaviors cannot be manipulated.

The first study in this dissertation aims to provide us with an understanding of a trader's behavior in an internal prediction market (see Figure 2.1) and answer the first major research question of this dissertation "how do traders behave in an internal prediction market?" Consequently, we do not intend to interfere or control traders' actual behavior in a market. Additionally, this dissertation addresses internal prediction markets, a contemporary management topic in real business world. Therefore, the use of a case study is appropriate.

3.3.2 Study 2 – Laboratory Experiments

The objective of the second study is to examine the effects of information transparency in a prediction market on trader's behavior and market prediction. Accordingly, this study aims to answer the second key research question of this dissertation - *how does information transparency in an internal prediction market influence market performance*? (see Figure 2.1).

To test such a casual model in the social sciences, experiments are usually adopted (Campbell and Stanley 1963; Cook and Campbell 1979; Shadish et al. 2002). An experiment refers to a study in which an intervention is deliberately introduced to observe its effects (Shadish et al. 2002). Particularly, in contrast to case studies, laboratory experiments allow researchers to deliberately divorces a phenomenon from its context, and thus, focus on only a few variables in a controlled environment (Yin 2003). Shadish et al. 2002 argued that this highly controlled environment of laboratory experiments assists researchers to determine and strengthen the causality. Therefore, we adopted laboratory experiments in this second study to test the casual effects of information transparency.

3.3.3 Study 3 - Field Experiments

The objective of the third study is to investigate the effects of different information transparency levels in a prediction market on trader's behavior and market performance (see Figure 2.1). Similar to the aforementioned laboratory study, this study answers the key research question – *how does information transparency in an internal prediction market influence market performance*? The results drawn from this study ought to complement the answers to the aforementioned research questions based on the laboratory experiments.

In contrast to the second study, this study aims to examine the phenomenon in a real business environment. As Harrison and List (2004) argued, laboratory experiments in isolation are necessarily limited in relevance for predicting field behavior, as unexpected behaviors may occur when control in the field is loosened. These unexpected behaviors in fact often indicate the key features of the research phenomenon that have been neglected in the lab. Therefore, we adopt field experiments in this third study.

Harrison and List (2004) defined a field experiment as one employs a nonstandard subject pool with field context in the commodity, task, or information set that the subjects can use in the environment where the subjects naturally undertake these tasks and do not know that they are in an experiment. They contended that field experiments have a methodological role, as they are substantively complementary to traditional laboratory experiments.

When laboratory experiments are combined with field experiments, they permit sharper and more convincing inferences generated from a broader context. From the perspective of engaged scholarship, Van de Ven (2007) also encouraged researchers to spend time doing field research, as field research brings researchers closer to the phenomenon they are studying and permits deeper learning and understanding of a research question or topic. Moreover, insight into the phenomenon drawn from the field work is likely to increase the chances that the research results will be eventually implemented by organizational practitioners (Rynes et al. 1999).

Consequently, we adopt field experiments in this dissertation to enhance the generalizability of the research findings as a whole.

CHAPTER 4 UNDERSTANDING TRADER'S BEHAVIOR: AN EXPLORATIVE CASE STUDY

4.1 INTRODUCTION

Traders are a fundamental element of a prediction market (Ho and Chen 2007). They have information about a future event and reflect their information in the trading of contracts in the market (Fama 1970; Muth 1961). A prediction market, thus, aggregates information from traders based on the market mechanism (Hayek 1945). Traders' behavior in the prediction market is, in turn, pivotal to the market, because trading activities entail the transmission and aggregation of information and eventually influence market performance. Consequently, traders' behavior has become a major research stream of prediction markets.

This dissertation focuses on internal prediction markets within a firm. The research on traders' behavior in internal prediction markets is underdeveloped. In Chapter 2, we reviewed current literature on internal prediction markets. Prior studies focused on market performance and most of them addressed the accuracy of the market prediction (e.g. Pethokoukis 2004; Plott and Chen 2002; Ortner 1998). The behavior of individual traders, however, has rarely been captured. Accordingly, we have constructed our first major research question about trader's behavior and this chapter aims to answer the following question:

$RQ_{main}1$: *How do traders behave in an internal prediction market?*

Internal prediction markets are characterized by such factors as small market size and low liquidity (Plott and Chen 2002; Cowgill et al. 2008; see Chapter 2). In terms of these specific characteristics, most existing studies on traders' behavior in internal prediction markets or small size prediction markets concentrate on traders' manipulation. These studies are particularly interested in the likelihood and effect of traders' manipulation and bias on information aggregation and the predictive accuracy of prediction markets (see Chapter 2).

Nevertheless, little research addresses the fundamental behavior of traders in the market, namely learning. In a prediction market, some traders have information about a future event, but some do not (Plott 2000). The former are referred to as informed traders; and the latter are referred to as uninformed traders. Markets are efficient, because information can be disseminated from the informed to the uninformed. This process is referred to as information aggregation (Gruca et al. 2005; Plott and Sunder 1982; 1988).

Information aggregation is processed through traders' trading activities. A trader's individual bids and asks on a contract represent the value he or she expects of it. Similarly, a transaction on a contract represents the aggregate expected value of the contract. These orders and transactions in turn become public information available in the market and other traders learn from it. Gradually, with an increased number of trades, information about a future event is disseminated from the informed to the uninformed. As a result, learning is an underlying behavior of traders in a prediction market. Consequently, this first study focuses on learning among traders in internal prediction markets.

Furthermore, most existing studies on traders' behavior are conducted in laboratory environments (e.g. Forsythe and Lundholm 1990; Hanson et al. 2006; Plott and Sunder 1982). Harrison and List (2004) have identified the constraints of laboratory experiment relative to predicting field behavior (see Chapter 3). In turn, it is crucial to investigate traders' behavior in a prediction market within a real business environment. Therefore, we conducted an explorative case study to examine the behavior of individual traders in internal prediction markets.

Several major findings are drawn from the case study. First, traders are generally not active in an internal prediction market. Employees of companies usually regard participation in internal prediction markets as additional work, and therefore, they may have limited time to participate. Second, traders learn from different information sources and incorporate what they learn into their trading activities, though the activities are limited. In turn, they keep updating their opinions of future events. However, the influence of one trader on others seems to be small. Third, employees' trading decisions are influenced most by the latest private information about a future event. Additionally, marginal traders and information cascades may be concurrent in an internal prediction market.

This study makes several theoretical and practical contributions to the body of research on prediction markets. First, our study extends the research on traders' behavior by investigating learning in the market. Second, we contribute to the adaptive learning theory by applying it in the context of prediction markets. Third, our research adds to the literature on prediction markets used in companies and the real business world. We particularly contribute to the exploration of traders' behavior in internal prediction markets. Finally, from the perspective of managerial implications, this multiple case study documents the reasons why traders do not actively participate in internal prediction markets, allowing practitioners to improve their market design and operation by taking practical issues into consideration.

The remainder of this chapter is organized as follows. First, we review the related literature on traders' learning in a prediction market. Second, we elaborate the research method adopted in this chapter. Third, we present and discuss the results drawn from this case study. Finally, we conclude this chapter by answering the corresponding research question.

4.2 THEORETICAL BACKGROUND

In this section, we introduce the theory of traders' behavior in a prediction market. We focus on traders' fundamental learning, which is reflected in their trading and interactive activities.

4.2.1 Adaptive Learning in Prediction Markets

Prediction markets are similar to financial markets. Traders in a prediction market are equivalent to investors in a financial market. Their decisions are almost always made under uncertainty. Learning, therefore, occurs as the flow of information on the costs and benefits of an investment decision reduce its uncertainty (Dixit and Pindyck 1994).

Rational expectations theory is the primary theoretical foundation of prediction markets (see Chapter 2). Rational expectations theory assumes that economic agents have full knowledge about the entire system in which they are operating (Muth 1961). This assumption leads to an asymmetry between the agents in the model and the econometrician who is estimating it, as the economist or econometrician knows less about the system than the agents (Sargent 1993). To eliminate this asymmetry, bounded rationality was proposed by Simon (1957) based on the assumption that agents behave like working economists or econometricians, who do not have complete information about an object (Sargent 1993). In addition, when taking time into consideration, the model of expectations is no longer static, but dynamic, in which things change with the passage of time and expectations adapt; hence, the name adaptive expectations (Cagan 1956; Sargent 1993). In other words, agents iteratively adjust their estimations of an object in order to diminish the discrepancy between the estimation and perceived reality from one period of time to the next (Sargent 1993).

Based on the idea of bounded rationality and adaptive expectations, Sargent (1993) suggested adaptive learning, which assumes that economic agents initially may not know the exact information they need to predict relevant outcomes. Nevertheless, the agents are willing and able to learn over time. As a result, the agents are able to keep updating their expectations based on the newly-received information. As Oliven and Rietz (2004) asserted, even biased traders may learn from market prices, and accordingly, they may update their expectations in ways that defeat the bias.

The learning that occurs in prediction markets is in fact adaptive learning. Traders are deemed to learn and keep updating their beliefs based on the latest information and reflect the updated information in their bids and asks (Bondarenko and Bossaerts 2000; Gruca et al. 2005; Rhode and Strumpf 2004). Notwithstanding non-market information, such as media news of a future event, traders learned from other individual expected values and the aggregate expected values of contracts inside a market (Davis and Holt 1993).

Empirical studies have demonstrated the occurrence of traders' learning in a prediction market. For instance, Lee and Moretti (2009) investigated the 2008 presidential election in the United States and found that market price appeared to react to the release of relevant information. This reaction indicated that traders in the presidential election market learned and incorporated the learned information into their predictions.

As information is disseminated through trades and learning is reflected in trades, active trading of contracts is desired. Therefore, we first examine the activity of traders in internal prediction markets. The first sub-research question is then as follows:

RQ 1-1: *How actively do traders take part in an internal prediction market?*

4.2.2 Dynamic Interactions between Traders in Prediction Markets

Chen et al. (2009) argued that learning in prediction markets is dynamic not only because of the adaptive mechanism but also the involvement of dynamic interactions between traders. First, traders may revise their own expectations on contracts based on learning from other traders in the market and adjust the bids or asks of the contracts accordingly.

Second, adjustments of bids and asks become new information for other traders to learn in the same market, and therefore lead other traders to revise their expectations on contracts. Hence, one trader's revision of bids or asks is not only the consequence of learning but also the cause of another trader's revision.

Moreover, the influence of one trader's revision can be extended when a succession of subsequent traders revise their bid or ask orders of the contract. In turn, dynamic interactions refer to a trader's revision of buy or sell orders on contracts as a consequence of learning and the cause of another trader's revision. In short, the presence of traders' dynamic interactions indicates that learning occurred in the market. Accordingly, we construct the second sub-research question as follows:

RQ 1-2: *To what extent do traders dynamically interact with each other in an internal prediction market?*

4.3 RESEARCH METHODS

In this section, we delineate the design of this explorative case study and describe the details of the prediction markets developed in this study.

4.3.1 Case Study Design

As stated in Chapter 3, this study aims to answer the first key research question of this dissertation, namely, "*How do traders behave in an internal prediction market?*" In line with Yin's (2003) guideline of case study designs, we first identified the aforementioned specific sub-research questions to be answered in this study based on the related literature review.

Subsequently, to apply replication logic (Hersen and Barlow 1976), we adopted multiple-case studies, examining traders in two different internal prediction markets According to Yin (2003), a multiple-case design, even a two-case design is preferred over a single-case design, as researchers have the possibility of direct replication. Conclusions independently drawn from these two cases will be more powerful than those coming from a single case alone.

We collected the data from a partnering company, in which two internal prediction markets were conducted in sequence. We partnered with an international financial company headquartered in the Netherlands and ranked in the Fortune Global 500. The two markets predicted domestic sales of a particular financial product during two different time periods. The primary motivation for the company to use internal prediction markets was its dissatisfaction with its conventional prediction mechanism.

This company used a "top-down" forecasting method to predict sales. According to the company, the forecasting method was complex and time consuming, and worked as follows:

The top management team proposed an initial prediction of sales, and then forwarded it to the lower level managers along the organizational hierarchy until it reached the regional sales managers. Some calibration of the initial prediction was expected in response to any objection raised during the forwarding procedure.

However, calibration rarely happened: lower level managers often just accepted the initial prediction. The company believes that its regional sales managers would make the most accurate predictions, as these managers have the most relevant and updated information about the products. Consequently, the company expected that involving those regional sales managers in internal prediction markets would reveal the best predictions. In turn, they conducted the aforementioned two internal prediction markets as their pilot study.

We chose this company because it thoroughly documented every action of each trader, such as a trader's log-in, buy orders, sell orders and transactions of a contract. Moreover, this company allowed us to conduct a follow-up questionnaire study to obtain supplementary information about the traders' behavior, for instance, why a trader did or did not take part in an internal prediction market. We expected that this follow-up study could help us gain a deeper understanding about the participation of employees in internal prediction markets.

The following sections describe the details of the two cases, including the market mechanism, contracts, traders, incentives and operations.

4.3.2 Market Mechanism

The partnering company established a web-based continuous double auction market to support both internal prediction markets. On a single web page, all the contracts in a market were available (see Figure 4.1). The web page was divided into four parts as follows:

In Part A, the highest buying price and the lowest selling price of each contract were displayed and traders could place buy or sell orders for each contract; in Part B, the historic transaction prices of each contract since the first transaction were exhibited in a line chart; in Part C, the last five transactions in the market were displayed, including contracts, shares transacted, prices and transaction time; and in Part D, an overview of the trader's buy and sell orders was provided, showing the status of an order, i.e. "executed" or "not executed" - "executed" means that the order had been successfully transacted; and "not executed" means that the order was pending.

This web-based prediction market platform was tested before the launch to ensure that traders would not experience any technical difficulties, which may have impeded motivation to participate.

4.3.3 Predicting Events and Contracts

The two markets were conducted in March and June 2007, and we refer to them in this study as the "March Market" and the "June Market".

The March Market predicted the annual sales of a particular financial product in 2007. The

June Market predicted the periodical sales of the same financial product during a particular campaign in 2007.

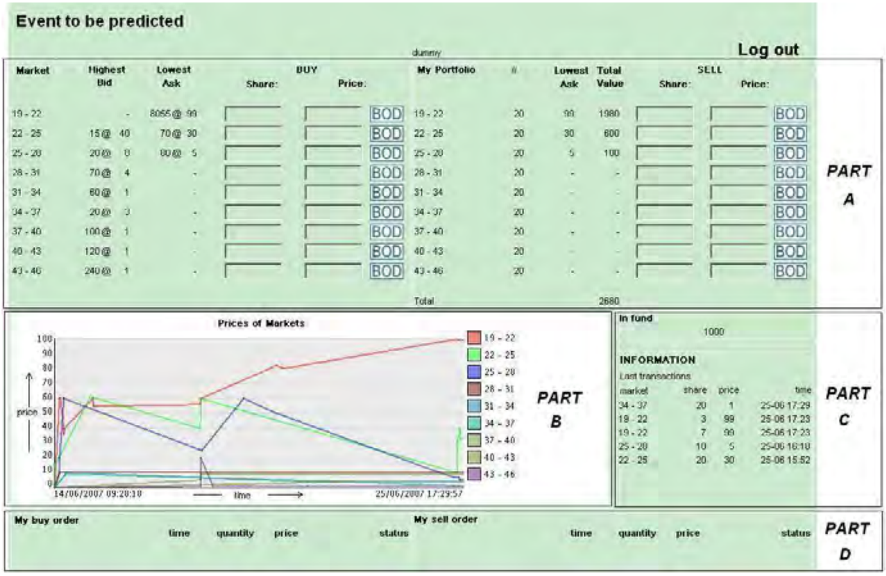

Figure 4.1 Screen Shot of a Prediction Market Web Page

The contracts represented the potential outcomes of the event being predicted in the market. To illustrate, we take an example of the contract "191-200" in the March Market. This contract represented that annual sales of the financial product in 2007 would lie in the range of 191 and 200 million euro. Tables 4.1a and 4.1b list the events being predicted, the contracts, and the corresponding representations in the March Market and the June Market, respectively.

The aforementioned potential sales outcomes were determined by the company's top management team based on their initial prediction. This initial prediction was usually used in the conventional "top-down" forecasting method.

Table 4.1a Contracts of the March Market

Events Predicted	*Contract*	*Representation of Contract*
Annual sales of a financial product in 2007	110-120	Sales will be between 110 and 120 million euro
	121-130	Sales will be between 121 and 130 million euro
	131-140	Sales will be between 131 and 140 million euro
	141-150	Sales will be between 141 and 150 million euro
	151-160	Sales will be between 110 and 120 million euro
	161-170	Sales will be between 161 and 170 million euro
	171-180	Sales will be between 171 and 180 million euro
	181-190	Sales will be between 181 and 190 million euro
	191-200	Sales will be between 191 and 200 million euro
	201-210	Sales will be between 201 and 210 million euro

Table 4.1b Contracts of the June Market

Event Predicted	*Contract*	*Representation of Contract*
Periodical sales of a financial product during a particular campaign in 2007	19-22	Sales will be between 19 and 22 million euro
	22-25	Sales will be between 22 and 25 million euro
	25-28	Sales will be between 25 and 28 million euro
	28-31	Sales will be between 28 and 31 million euro
	31-34	Sales will be between 31 and 34 million euro
	34-37	Sales will be between 34 and 37 million euro
	37-40	Sales will be between 37 and 40 million euro
	40-43	Sales will be between 40 and 43 million euro
	43-46	Sales will be between 43 and 46 million euro

4.3.4 Traders

Thirty-four regional sales managers were invited to trade in the internal prediction markets. The company believed that they possessed the most relevant sales information about the product. These participants were located in 13 different regions within the Netherlands. In turn, they were thought to bring their own information regarding sales in their regions to the prediction markets. In other words, heterogeneity of information held by traders presumably existed in these two prediction markets.

4.3.5 Incentives

The company decided to offer monetary incentives. The amount of cash reward per market was €10 multiplied by the number of invited traders. As 34 regional sales managers were invited to take part in the internal prediction markets, the eventual award was €340 per market. When the actual sales results were unveiled, the trader who had the most shares of the contract that corresponded to the actual sales would receive the bonus of €340.

4.3.6 Operations

Each market was executed during a period of 12 calendar days, starting from 09:00 on the first day till 18:00 on the last day. To increase participation, the traders were allowed to access the markets 24 hours a day, including weekends.

A plenary introduction session, with full attendance, was given before the first prediction market. In the introduction session, the structure of the market mechanism, the event being predicted in the market, and the incentives were explained in detail; the operation of the web-based trading platform interface was demonstrated; and a special question and answer session was arranged in which traders were allowed to ask or clarify any issues regarding the internal prediction markets.

Although participation was anonymous, each trader was assigned a subject identification number and a log-in account. In the prediction markets, a trader's subject identification number was never revealed. Therefore, a trader was not able to trace the behavior of others within the same prediction market.

When the prediction market started, all the traders received an endowment that contained 1,000 points play money and 20 shares per contract to initiate trades.

4.3.7 Follow-up Questionnaire Survey

After the two markets closed, we conducted a questionnaire survey together with the partnering company. The questionnaire (see Appendix I) was sent to all the traders, namely, the 34 regional sales managers, by email.

The questionnaire entailed two major objectives. One objective was to examine the participation activity of a trader. For instance, how often a trader took part in the prediction markets. The other objective was to investigate the trader's use of various information sources. Using a five-point Likert scale (1= never, 5= always), the trader was asked to rate the extent to which an information source contributed to their trading decisions.

4.4 MEASURES

In this section, we focus on traders' behavior in an internal prediction market. The measurement of traders' behavior concentrates on traders' participation activity and dynamic interactions. This section elaborates the measurement of these two variables.

4.4.1 Traders' Participation Activity

We first identified the number of active traders in a market. Active traders refer to the traders who place at least one buy or sell order in a prediction market (Berg et al. 2008; Cowgill et al. 2008). As traders contribute their information to the market when and only when they incorporate their information into their trading activities, the number of active traders should be identified when measuring the traders' activity.

Subsequently, we examined the traders' participation activity at the contract level. We measured the number of active traders, the number of transactions, and the number of shares traded. According to existing research on prediction markets, these are the key indicators measuring the traders' activity, particularly in an internal prediction market (Berg et al. 2008; Chen et al. 2009; 2010; Forsythe et al. 1992).

Finally, we investigated activity at the individual trader level. We measured several key indicators, including the average number of buy orders/sell orders, the average number of shares in buy orders/sell orders, the average number of transactions and the average number of shares traded (e.g. Chen et al. 2009; 2010; Forsythe et al. 1992; Oliven and Rietz 2004).

4.4.2 Traders' Dynamic Interactions

The measurement of traders' dynamic interaction adapts from Chen et al. (2009), consisting of two dimensions, namely trader's self-revision and trader's influence on others. Trader's self-revision is measured at the individual trader level and trader's influence on others is measured at the contract level.

The details of the measurement of trader's self-revision are as follows. Let $V_{ij} = [V_{ij}^l, V_{ij}^u]$ denote a range containing trader *i*'s estimation for contract *j*, where V_{ij}^l is the lower bound and V_{ij}^u is the upper bound. V_{ij}^l and V_{ij}^u can be captured when trader *i* places his or her first buy order and sell order of contract *j*. As traders can observe individual bids, asks and aggregate behavior of other traders in a prediction market, traders may revise their estimation accordingly. If in the following order, trader *i* buys or sells contract *j* at a different price from the previous one, we term this "revision behavior" for trader *i* and refer to this new buy or sell order as a "self-revision".

Furthermore, we operationalize two measures of "self-revision", i.e. Type I and Type II. Type I self-revision is identified as long as trader *i*'s following order price is different from the previous one on the same contract; and Type II self-revision occurs when there is at least a 5% difference in the price of trader *i*'s order compared to his or her previous order for the same contract.

With regard to the trader's influence on others, we consider all four alterative measures of "influential orders" developed by Chen et al. (2009). Table 4.2 presents these four alternative operational definitions.

4.5 RESULTS

This section delineates the results of traders' participation activity and traders' dynamic interactions. The results drawn from the follow-up questionnaire survey are presented throughout the discussion of the aforementioned traders' behavior to provide supplementary evidence. We received 17 valid responses to the questionnaire for the March Market and 16 to the June Market, representing 11 sales regions. In the end of this section, we discuss the additional finding of information cascades in this case study.

Table 4.2 Alternative Operational Definitions of Influential Orders (Adapted from Chen et al. 2010, p. 59)

Operational Definition	*Definition*
1-influential	A buy or sell order is 1-infuential if the next buy or sell order of the same contract is from a different trader and is also a "self-revision" orders in the same direction.
2-influential	A buy or sell order is 2-influential if the next two consecutive buy or sell orders of the same contract are from two different traders and are also "self-revision" orders in the same direction.
3-influential	A buy or sell order is 3-influential if the next three consecutive buy or sell orders of the same contract are from three different traders and are also "self-revision" orders in the same direction.
2Out3-influential	A buy or sell order is 2Out3-influential if the next three consecutive buy or sell orders of the same contract are from three different traders and two of the three are also "self-revisions" orders in the same direction.

4.5.1 Traders' Participation Activity

Active traders numbered 30 in the March Market and 18 in the June Market. More than half of the invited regional sales managers participated in the internal prediction markets. Particularly, in the March Market, 30 out of 34 regional sales managers became active traders. The percentage reached 88%, considered high in internal prediction markets. In the June Market, the percentage of active traders dropped to 52% (18 out of 34).

In light of the statement that traders in a prediction market sometime appear to be motivated by curiosity (Borison and Hamm 2009), this drop was probably due to the change of the traders' interest and curiosity about the prediction markets. According to the top management team of the company, prediction markets were new to the traders. They had no experience with participation in prediction markets. Therefore, the March Market, as the first experience, motivated the traders' to take part. However, those regional sales managers were no longer motivated by curiosity to trade in the second market. In Google's prediction markets, there was also a gradual decline in interest among existing traders (Dye 2008).

Table 4.3 exhibits the statistics for traders' activity at the contract level in the two internal prediction markets. "Number of active traders" revealed that a trader did not trade on all contracts in an internal prediction market. For instance, there were 30 active traders in the March Market. However, none of the contracts in the March Market received buy orders or sell orders from all 30 traders. The average "percentage of active traders" further illustrated that a single contract received buy or sell orders from approximately 60% active traders in a market. Chen et al. (2009) obtained similar results from their study. They conducted two internal prediction markets to evaluate early stage technology and each market had 17 contracts. According to their analyses, no contract received the full participation from all the active traders. The average percentage of active trader per contract was approximately 60% as well.

"Number of transactions" showed that the traders in the two markets were not active. The average "number of transactions" for the March Market indicated that less than two transactions occurred per trade day on each contract ($Mean_{nr\_transaction}$ = 18, trade day = 12). The same measure for the June Market showed that participation was even lower ($Mean_{nr\_transaction}$ = 9), implying that on some trade days (trade day = 12), there were no transactions of a contract at all. The low occurrence of transactions was due to few buy and sell orders from the traders (see Tables 4.4a and 4.4b).

Tables 4.4a and 4.4b summarize the statistics for traders' activity at the individual level in the March Market and the June Market. The average "number of buy orders" (March Market: $Mean_{nr\_buy\_orders}$ = 16, June Market: $Mean_{nr\_buy\_orders}$ = 9) and "number of sell orders" (March Market: $Mean_{nr\_sell\_orders}$ = 16, June Market: $Mean_{nr\_sell\_orders}$ = 9) showed that an active trader on average placed no more than two buy or sell orders per trade day in both markets (trade day = 12).

The maximum number of these measures illustrated that even the most active trader in the March Market placed no more than eight buy or sell orders in total per trade day ($Max_{nr\_buy\_orders}$ = 51, $Max_{nr\_sell\_orders}$ = 43); and in the June Market, the most active trader placed less than six buy or sell orders in total per trade day ($Max_{nr\_buy\_orders}$ = 41, $Max_{nr\_sell\_orders}$ = 31).

To summarize, the results drawn from the analyses of trader's activity at the contract and the individual trader level showed that traders did not actively participate in the internal prediction markets.

Table 4.3 Summary Statistics for Traders' Activity at the Contract Level in the March Market and the June Market

Market	*Contract*	*Number of active traders*	*Percentage of active traders*	*Number of transactions*	*Number of shares traded*	*First trade day*	*Last trade day*	*Minimum transaction price*	*Maximum transaction price*
March	110-120	20	0.67	19	250	Day 3	Day 11	1 point	25 point
	121-130	19	0.63	21	265	Day 3	Day 10	10 point	30 point
	131-140	22	0.73	31	371	Day 1	Day 11	20 point	90 point
	141-150	20	0.67	28	327	Day 1	Day 11	15 point	80 point
	151-160	20	0.67	25	395	Day 1	Day 11	18 point	50 point
	161-170	20	0.67	19	253	Day 1	Day 11	5 point	50 point
	171-180	16	0.53	12	140	Day 4	Day 10	24 point	48 point
	181-190	13	0.43	2	40	Day 4	Day 9	14 point	30 point
	191-200	14	0.47	3	60	Day 1	Day 3	20 point	25 point
	201-210	19	0.63	24	620	Day 1	Day 11	1 point	18 point
	Average	*18*	*0.61*	*18*	*272*				
June	19-22	16	0.89	22	175	Day 1	Day 12	35 point	99 point
	22-25	12	0.67	17	207	Day 1	Day 12	10 point	61 point
	25-28	13	0.72	14	170	Day 1	Day 12	5 point	60 point
	28-31	13	0.72	3	50	Day 1	Day 8	10 point	35 point
	31-34	9	0.50	4	80	Day 1	Day 11	3 point	10 point
	34-37	8	0.44	4	80	Day 1	Day 12	1 point	9 point
	37-40	11	0.61	1	20	Day 9	Day 9	4 point	4 point
	40-43	10	0.56	4	80	Day 5	Day 5	5 point	10 point
	43-46	13	0.72	16	330	Day 5	Day 12	1 point	20 point
	Average	*11*	*0.65*	*9*	*132*				

Table 4.4a Summary Statistics for Traders' Activity at the Trader Level in the March Market

Measurement	*N*	*Maximum*	*Minimum*	*Mean*	*Std. Deviation*	*Median*
Number of buy orders	30	51	1	16	14	11
Number of shares in buy orders	30	1244	30	298	327	158
Number of sell orders	30	43	1	16	13	12
Number of shares in sell orders	30	915	20	289	279	175
Number of transactions	30	58	0	12	13	8
Number of shares traded	30	1324	20	285	324	179

Table 4.4b Summary Statistics for Traders' Activity at the Trader Level in the June Market

Measurement	*N*	*Maximum*	*Minimum*	*Mean*	*Std. Deviation*	*Median*
Number of buy orders	18	41	1	9	11	5
Number of shares in buy orders	18	8155	10	644	2012	73
Number of sell orders	18	31	1	9	8	8
Number of shares in sell orders	18	786	5	165	185	120
Number of transactions	18	48	0	9	11	6
Number of shares traded	18	874	10	148	210	100

As introduced in section 4.3.6, the company allowed trading in the market 24 hours a day, 7 days a week in order to increase activity, assuming that traders would take part in the internal prediction markets after work. The results, however, revealed that no one traded after work (namely, between 18:00 and 09:00 per trade day) or during weekends. The evidence can be drawn from Table 4.3. According to this table, the last trade day of the March Market was Day 11, and yet, this market ran for 12 days. However, no trade occurred on Day 12, which, coincidently, fell on the weekend. Usually the last trade day is busy, as the most updated information is available and traders would like to take the last trading opportunity to make profit in the market. A number of prior studies have asserted that the most relevant information comes in the last trade days, and therefore, researchers usually calculate the market prediction based on the last trade price or the last several trade prices (Berg et al. 2003a; 2003b; 2008; Servan-Schreiber 2004). The situation in the June Market supported this argument, as quite a few transactions occurred on the last trade day, i.e. Day 12, which was a weekday (see Table 4.3).

A possible explanation is that the regional sales managers regarded participation in the internal prediction markets as a part of their job, though participation was not obligatory. In turn, they did not spend their private time taking part in the markets. Hanson (2006) emphasized that participation in an internal prediction market requires that employees allocate time and effort away from their regular work duties. When a proper incentive is missing, employees do not bother to trade. The evidence drawn from the questionnaire further supported this explanation.

According to the data collected from the questionnaire, the traders identified lack of time as the major reason that they did not actively participate in the internal prediction markets. Although only eight traders responded to the question "Why would you not participate in the markets?" (this is the translation of question No. 7 in the questionnaire, see Appendix I), seven of them gave a similar reason of limited time for participation. These answers have been translated from Dutch into English and are briefly quoted in Table 4.5.

These quotations from the traders' responses supported the aforementioned explanations that the sales managers considered participating in the prediction markets only during their work time; participation was a part of the company "policy"; and taking part in the prediction markets was not the priority in their work.

Table 4.5 Traders' Responses to the Question about the Major Reason for Not Participating in the Internal Prediction Markets

Traders	*Quotations of Traders' Answers*
1	"I do not see the positive effects on my sales by participating in the markets. Participation in fact cost my time."
2	"It [participation] cost me too much time. I participated because the policy required me do so."
3	"I am not attached with this game."
4	"The idea is good. But I do not have time to explore it further."
5	"Frankly speaking, it was too hectic recently. I didn't have time to participate. My contribution is probably not very important."
6	"To be honest, I am very busy with visiting customers, explaining products, and troubleshooting. There are 20 to 25 outstanding emails in front of me. This [participation in the prediction markets] is not my priority."
7	"I don't feel like participating, as it takes too much time."

We noticed that one trader gave a unique reason for not participating in the internal prediction markets. He said that *"…other traders in the markets were not active. Many of my orders cannot be matched in the markets. I logged in very often. However, I found that my orders were always pending….*" This sales manager's answer in fact brought the problem of low activity to light. Kambil and Van Heck (2002) contended that a market must have liquidity to function, which requires a certain minimum level of traders' activity. Therefore, this result actually emphasized the importance of traders' activity in an internal prediction market. When only a few traders behave actively, they may finally become inactive due to unavailability of trading with others.

4.5.2 Traders' Dynamic Interactions

Table 4.6 summarizes the statistics for traders' self-revisions, measured at the individual trader level. "Number of self-revision (Type I)" showed the number of buy or sell orders with a different price compared to the previous order placed by the same trader for the same contract. According to this table, in the March Market, on average, each trader placed 15 buy or sell orders with a different price compared to his or her previous order for the same contract; and in the June Market, each trader, on average, made 7 self-revisions for the same contract.

"Number of self-revisions (Type II)" showed the number of buy or sell orders with at least 5% difference in price compared to the previous order placed by the same trader for the same contract. Table 4.6 shows that on average, a trader placed 14 Type II buy or sell orders in the March Market and made 6 Type II self-revisions in the June Market.

The comparison between the number of Type I and Type II self-revisions disclosed the tiny difference between these two types in both markets: the average number of Type II self-revisions was just one smaller than Type I in both the March Market and the June Market (March Market: $Mean_{self\_rev\_I} = 15$, $Mean_{self\_rev\_II} = 14$; June Market: $Mean_{self\_rev\_I} = 7$, $Mean_{self\_rev\_II} = 6$).

This tiny difference indicated that almost all self-revision from a trader for a contract entailed at least 5% difference of price compared to his or her previous buy or sell order. In this case, 5% is considered statistically significant. Moreover, the comparison to the average total number of buy or sell orders at the trader level (March Market: $Mean_{buy\_sell\_orders} = 32$, June Market: $Mean_{buy\_sell\_orders} = 18$) demonstrated that self-revisions accounted for approximately 50% of the orders placed by the traders (see Figure 4.2). In other words, half of the buy or sell orders entailed an update of traders' opinions of future events. Therefore, it can be argued that the traders in these internal prediction markets learned and incorporated their learning into their personal predictions, confirming our predecessors' findings (Bondarenko and Bossaerts 2000; Gruca et al. 2005; Rhode and Strumpf 2004).

With regard to a trader's influence on others, measured at the contract level, Table 4.7 displays the statistics for four alternative influential orders. In accordance with this table, the mean values of different types of influential orders show that there were more 1-influential orders than any other influential orders in both markets (March Market: $Mean_{1\text{-influential}} = 4 > Mean_{2\text{-influential}} = 1 > Mean_{3\text{-influential}/2out3\text{-influential}} = 0$; June Market: $Mean_{1\text{-influential}} = 1 > Mean_{2\text{-influential}} = 0$). In turn, it can be concluded that one trader's influence on another concentrated on the one degree influence.

Table 4.6 Summary Statistics for Traders' Self-revision in the March Market and the June Market

Market	*Measurement*	*N*	*Maximum*	*Minimum*	*Mean*	*Std. Deviation*	*Median*
March	Number of self-revisions (Type I)	30	48	0	15	17	7
	Number of self-revisions (Type II)	30	45	0	14	16	7
June	Number of self-revisions (Type I)	18	31	0	7	10	2
	Number of self-revisions (Type II)	18	28	0	6	9	1

Table 4.7 Summary Statistics for Influential Orders in the March Market and the June Market

Market	*Measurement*	*N*	*Maximum*	*Minimum*	*Mean*	*Std. Deviation*	*Median*
March	Number of 1-influential orders	10	18	0	4	5	2
	Number of 2-influential orders	10	2	0	1	0.7	0
	Number of 3-influential orders	10	1	0	0	0.3	0
	Number of 2Out3-influential orders	10	2	0	0	0.7	0
June	Number of 1-influential orders	9	7	0	1	2	0
	Number of 2-influential orders	9	1	0	0	0.3	0
	Number of 3-influential orders	9	*	*	*	*	*
	Number of 2Out3-influential orders	9	*	*	*	*	*

*: the value has been omitted due to the constant zero.

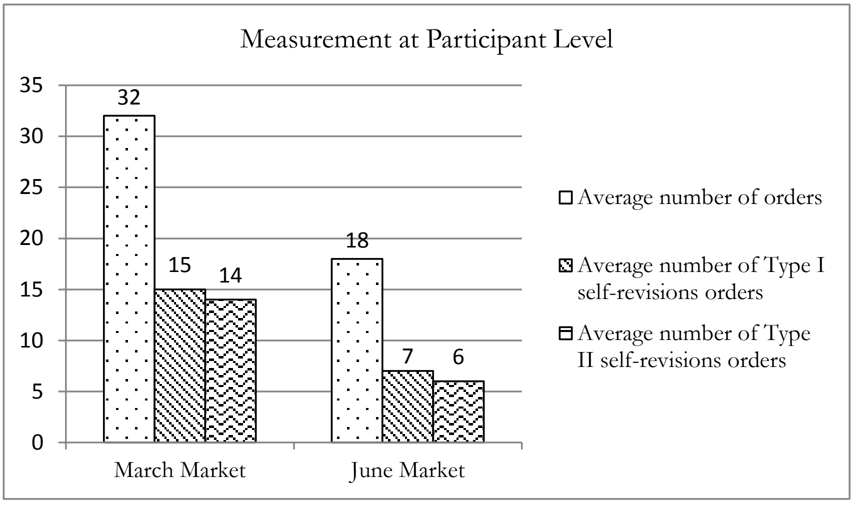

Figure 4.2 Measurement at Trader Level in the March Market and the June Market

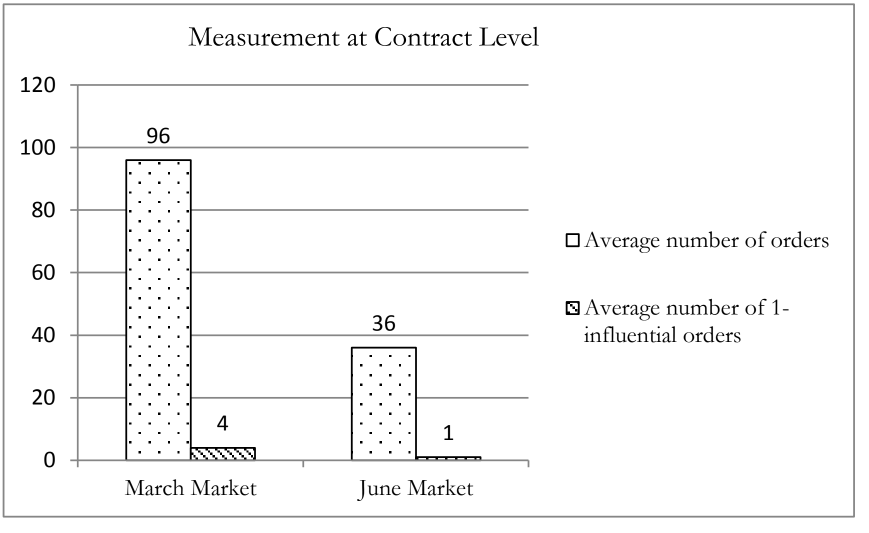

Figure 4.3 Measurement at Contract Level in the March Market and the June Market

However, the influence of a trader on another did not seem to be large. Even though one degree influential orders occurred most, the occurrence was limited. To be specific, the average number of 1-influential orders in the March Market ($Mean_{1\text{-influential}} = 4$) indicated that there were on average four buy or sell orders followed by another order of the same contract, which was from a different trader and was also a self-revision for that trader in the same direction in this market; and in the June Market, there was only one 1-influential order per contract ($Mean_{1\text{-influential}} = 1$). Comparing to the average number of buy or sell orders at contract level (March Market: $Mean_{buy\_sell\_orders} = 96$; June Market: $Mean_{buy\_sell\_order} = 36$), these 1-influential orders accounted for only 4% of all the orders in the March Market and less than 3% the June Market (see Figure 4.3).

Other influential orders became extremely scarce. Although there were two degree influences of an order captured in both markets, the average and the maximum "number of 2-influtneial orders" in the March Market and the June Market (March Market: $Mean_{2\text{-influential}} = 1$, June Market: $Max_{2\text{-influential}} = 1$), demonstrated that while there was on average one 2-influential order per contract in the March Market, there was only a single 2-influential order of some contracts in the June Market. This result revealed that few orders were followed by two consecutive orders of the same contract from two different traders, which were also self-revisions in the same direction.

Moreover, Table 4.7 illustrated that in the March Market, there was only one 3-influential order and two 2Out3-influential orders of some contracts ($Max_{3\text{-influential}} = 1$, $Max_{2Out3\text{-influential}} = 2$). In the June Market, there was not even a single 3-influential or 2Out3-influential order (the value for each measure remained zero). The scarcity of these influential orders disclosed that an order was rarely followed by more than two consecutive orders of the same contract from different traders that were also self-revisions in the same direction.

The aforementioned analyses of a trader's self-revisions implied low influence of a trader's order on others. A possible reason is that the traders kept learning about the future event and incorporating the new information into their estimation (Bondarenko and Bossaerts 2000; Gruca et al. 2005; Guo et al. 2006; Ho and Chen 2007; Rhode and Strumpf 2004). Therefore, there were always changes in the direction of one trader's self-revision orders, and hence, one order's influence on others did not remain to a large extent.

The empirical evidence to support this explanation was drawn from the questionnaire survey. In the survey, we asked the traders to rate the importance of different information sources for their trading decisions. Figures 4.4a and 4.4b exhibit the average importance of these information sources.

According to the figures, “recent regional sales” and “recent overall sales” were considered more important than other information sources by the traders. In the March Market, “recent regional sales” was rated 4.18; and in the June Market, this information source was rated 4.19. In both markets, the traders identified the recent regional sales of the financial products being predicted most important information source in their trading decisions. Similarly, in the March Market and the June Market, the rates of importance given to the “recent overall sales” were considerably high, reaching 4 and 3.75, respectively. These high rates manifested that the traders took the recent sales of the financial products in the Netherlands into consideration to a large extent.

4.5.3 Additional Findings of Information Cascades

An additional finding of information cascades drew our attention in this case study. An information cascade refers to a process by which people influence one another, so much so that traders ignore their private knowledge and rely instead on the publicly stated judgments of others (Sunstein 2006b). Information cascades arise when individuals rationally choose identical actions despite having different private information (Alevy et al. 2007). This phenomenon is associated with traders’ learning. Banerjee (1992) and Bikhchandani et al. (1992) argued that repeated learning may lead individuals to forego their private information and duplicate their predecessors’ choices. Anderson and Holt (1997) and Çelen and Kariv (2004) showed evidence of information cascades in laboratory environments, where researchers can observe when decision-makers abandon their private information.

Nonetheless, in a real business environment, we can only suspect the phenomenon of information cascades, as we cannot observe whether a trader in a prediction market has chosen to ignore his or her private information to follow the actions of those ahead of them.

In the June Market, when the transaction price of contract “19-22” suddenly turned to 99 points (see Table 4.3, *Maximum transaction price* of this contract), it became the most striking information signal to other traders. It may have stimulated others to believe that some people in the same market must have special inside information. Especially, during the time when the June Market was running, there was much negative news in media about the financial product being predicted. Contract “19-22” corresponded with the lowest sales of that financial product. It is presumed that the combined effect of the media and market information encouraged information cascades in this market. Therefore, there were quite a few prompt responses (i.e. buying at 99 points) to this signal.

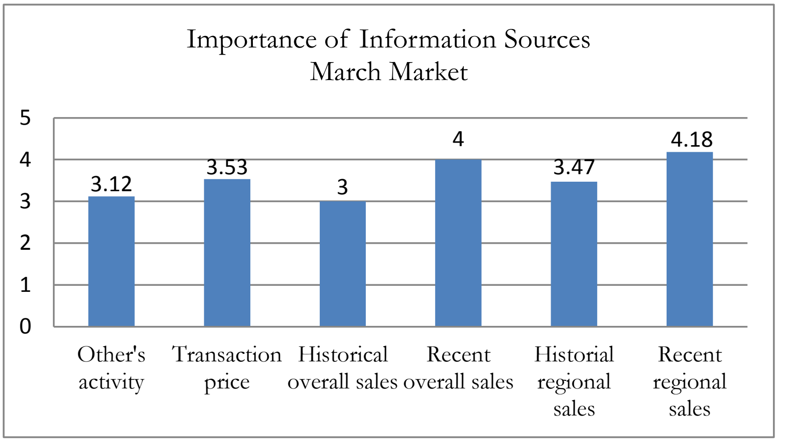

Figure 4.4a Average Importance of Different Information Sources in the March Market

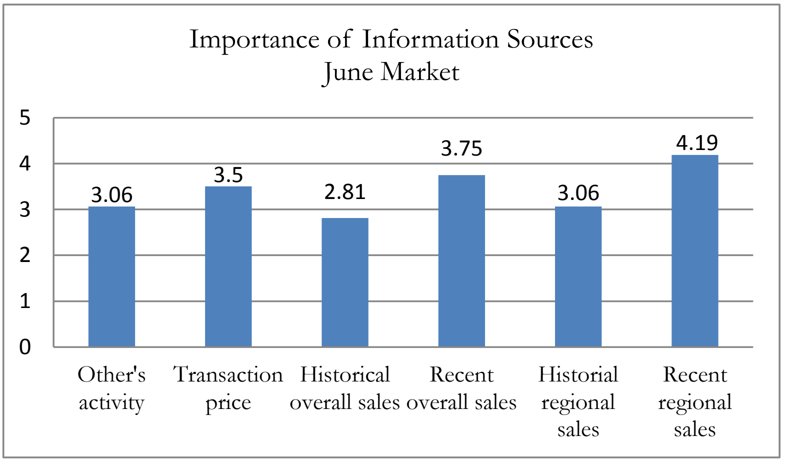

Figure 4.4b Average Importance of Different Information Sources in the June Market

Bikhchandani et al. (1992; 1998) stated that information cascades often explain why small shocks can lead to dramatic shifts in mass behavior and how with little information, individuals may all converge on one action. Particularly, when a trader decides that the previous trader has a more powerful signal than everyone else, he or she is likely to follow the previous trader's action (Smith and Sorensen 2000). In the June Market, the striking increase of the market price probably convinced the traders that other traders had information they lacked, and therefore, they acted alike. Therefore, we suspected that information cascade occurred in the June Market.

Information cascades are not necessarily negative. However, when individuals focus on the wrong kinds of information from the market place, they are led to make mistakes with how they update their information (Kauffman et al. 2010). In the June Market, the suspected information cascade eventually undermined market performance, because contract "19-22" did not correspond to the actual sales outcome and its high transaction price became a misleading signal.

The aforementioned evidence regarding traders' responses to the transaction price of a contract in fact indicated that traders were sensitive to the prices of contracts, confirming that traders in a market learn from signals and constantly update their beliefs (Bondarenko and Bossaerts 2000; Gruca et al. 2005; Rhode and Strumpf 2004). Unfortunately, as discussed above, traders sometimes refer to the wrong signal, and thus the market and the traders will be misled.

Nevertheless, having investigated all buy and sell orders of contract "19-22", we found, surprisingly, that one trader placed two sell orders of this contract at a much lower price (i.e. 26 points) and another two traders placed buy orders of this contract at prices lower than 99 points. These orders can be considered as a correction from the market.

Unfortunately, these correction orders were placed on the last trade day and the new buy orders were not shown on the market platform due to lower than the highest outstanding bid at 99 points. As a result, the transaction price of contract "19-22" ended at 99 points and was not corrected. Since the market prediction was based on the transaction prices of the contracts, the eventual forecasting accuracy of the June Market was influenced. The traders who attempted to correct the market were likely to be more rational, and therefore, they could have acted as "marginal traders" (Forsythe et al. 1992; Oliven and Rietz 2004) in the June Market. Given enough time, they could have driven the market to be more efficient (Forsythe et al. 1999).

4.6 CONCLUSIONS

While there is an increased interest in use of prediction markets inside companies, many companies are grappling with the practice of management due to various uncertainties, such as incentives for traders and the potential ramification of prediction markets (Kiviat 2004).

Particularly, the understanding of traders' behavior in internal prediction markets remains limited. This case study, therefore, aims to explore this area and answer the major research question "*How do traders behave in an internal prediction market?"* We address two specific aspects to answer this question. One aspect is the traders' activity level, and the other aspect is the interactions between the traders.

The results, drawn from two internal prediction markets about the sales of a financial product in an international financial company in the Netherlands, are consistent. This case study reveals several key findings.

First, the traders' activity level is generally low. In reality, the number of active traders in an internal prediction markets is difficult to control, though a company may have developed various incentive mechanism to encourage its employees to actively participate. Employees, as the traders of internal prediction markets, are usually confronted with limited time in trading. Participation in the markets requires employees to allocate time and effort from their regular work. The entertainment value, which drives traders to actively participate in public prediction markets (Wolfers and Zitzewitz 2004), does not work in internal prediction markets. There could even be a quick decline in interest among existing traders (Dye 2008), particularly when the market size is small (less than 30 traders) and the markets run in parallel or continuously.

Second, traders actively learn from different information sources and incorporate new information into their trading. Employees may not trade actively, but they seem to update their opinions whenever they trade. Particularly, employees consider the newly acquired private information most important in their trading. This supports the salient ability of prediction markets to aggregate inside information from dispersed individuals (Plott 2000).

Third, one trader's order may impact another trader's order, leading to an identical change of a different trader's opinion. However, the extent of this influence is not likely to be large. It rarely happens that one employee's order may influence more than two subsequent orders from different employees, as employees are more inclined to revise their opinions based on private information.

Nevertheless, when a trader selects an unusual price of an order, it could lead to an information cascade in an internal prediction market. Traders learn from signals, such as prices of contracts (Bondarenko and Bossaerts 2000; Gruca et al. 2005; Rhode and Strumpf 2004). An unusual price of a bid, ask or transaction may lead employees to believe that someone has special private information about the future event, and therefore, quickly respond to this action, leading to an information cascade. When the information is in fact inaccurate, the effect of this information cascade becomes negative on the market prediction. Marginal traders, however, are able to discern the quality of the unusual signal. Their trading turns to correct the market, though its effect may not immediately emerge.

Moreover, as illustrated by the prior experiences of prediction markets inside companies such as HP and Siemens, motivating employees to trade is a major challenge (Wolfers and Zitzewitz 2004). This study discloses that although employees show interest and willingness to participate, they are not likely to do so during their private time. As a result, 24/7 access to the market does not increase the participants' trading activities in an internal prediction market. The underlying reason is that employees regard participation as a part of their work, and therefore, they are only willing to join during the work hours and when there are no other job-related tasks with priority. Therefore, companies may consider allocating time for employees to trade in the markets. This approach was adopted in our following field experiment (see Chapter 6) with satisfying effect.

CHAPTER 5 INFORMATION TRANSPARENCY AND MARKET PERFORMANCE: A LABORATORY EXPERIMENT

5.1 INTRODUCTION

The increased use of prediction markets is attributed to the pervasiveness of IT. Malone et al. (1987) foretold that there would be a shift to proportionately more use of markets due to information technologies. Web-based prediction markets eliminate the temporal and spatial constraints of participation: traders all over the world can access a web-based prediction market anytime, anywhere.

Advanced technologies have not only enabled web-based prediction markets but also enhanced information transparency in markets, such as the distribution of various types and amounts of market information (Granados et al. 2010). In turn, in most current prediction markets, different types of information, such as outstanding bids and asks and transactions, are usually made available to traders. Like the public or internal prediction markets mentioned in Chapter 2, the two internal prediction markets in our previous case study demonstrated the adoption of transparent information in the market.

Information transparency refers to the level of availability and accessibility of market information to traders (Zhu 2004). The effect of information transparency on different markets, such as B2B and B2C, varies (Granados et al. 2008; 2010; Zhu 2002). However, to date, little work has been done on the effects of information transparency on prediction markets. Since the possibility and use of information transparency could be extensive in the prediction market, in this dissertation, we examine the effects of information transparency on prediction market performance. As discussed in Chapter 1, the second major research question of this dissertation is as follows:

$RQ_{main}2$: *How does information transparency in an internal prediction market influence market performance?*

Based on information elements, price transparency is identified as a specific type of information transparency (Granados et al. 2010). Price transparency refers to the revelation of information about prices, such as current market prices, quotes and historical transaction prices (Granados et al. 2006; 2010; Soh et al. 2006). In prediction markets, prices indicate information and encompass information aggregation and dissemination (Ho and Chen 2007) and information aggregation is the fundamental function of a prediction market. Therefore, in this dissertation, we focus on price transparency.

In the previous explorative case study, we observed that internal prediction markets are confronted with limited participation. Particularly, the number of participants actively trading in the market may be constrained and very limited. Constrained traders' participation has been identified as a serious disadvantage of prediction markets (Hanson et al. 2006; Sunstein 2006a). Unfortunately, internal prediction markets are usually characterized by this issue (Plott and Chen 2002; Cowgill et al. 2008). Therefore, our research focus and designs in this chapter are based on this common situation of internal prediction markets.

Furthermore, the literature review in Chapter 2 discussed two aspects of market performance; information aggregation and market prediction. In this laboratory experimental study, we examine these two aspects in terms of information aggregation efficiency and predictive accuracy. Information aggregation efficiency reflects the traders' agreed opinion, and forecasting accuracy is critical for decisions. The laboratory experiments allow us to assess both aspects of market performance.

The objective of this chapter, in turn, is to investigate the effect of price transparency on the information aggregation efficiency and the predictive accuracy of internal prediction markets through trader's behavior. The following two sub-research questions are as follows:

RQ 2-1: *How does price information transparency in an internal prediction market with a limited number of actively trading traders influence the traders' behavior and further influence market information aggregation efficiency*?

RQ 2-2: *How does price information transparency in an internal prediction market with a limited number of actively trading traders influence the traders' behavior and further influence market predictive accuracy*?

This chapter adds to the growing literature on prediction markets, particularly internal prediction markets within companies that include a limited number of actively trading participants. The laboratory experiments empirically test our hypotheses. The evidence resulting from the experiments shows that the revelation of price information undermines traders' participation and learning activity, when only a few traders are actively participating in an internal prediction market. This further leads to a negative effect on market information aggregation efficiency as well as market predictive accuracy, as higher information aggregation efficiency and increased predictive accuracy require higher levels of trader participation and adaptive learning. We therefore suggest concealing certain price information, such as quotes, in small-scale internal prediction markets.

One key contribution of this research is to extend current studies on information transparency by investigating its effect in new types of markets. Moreover, this paper adds information transparency, particularly price transparency, to prediction market design. The examination of traders' behavior in this research enhances the understanding of why and how their specific activities influence market predictive accuracy. Furthermore, we develop a method to measure information aggregation efficiency. This indicator allows practitioners to assess prediction market performance prior to the revelation of the actual results of the future event. Consequently, they can determine whether or to what extent they can make a decision based on the market forecast. Moreover, our study provides practitioners with an alternative market design in terms of information transparency to tackle limited participation in an internal prediction market.

The chapter is organized as follows. We first discuss the relevant theoretical foundations and construct the hypotheses based on this theoretical background. Subsequently, we elaborate on the research design of the laboratory experiments. Thereafter, we present the results from our empirical studies and validate the hypotheses. Finally, we conclude our research findings and answer the research questions.

5.2 THEORETICAL BACKGROUND

In this section, we introduce the theoretical foundations of this laboratory experiment and develop our hypotheses.

5.2.1 Information Transparency and Trader's Behavior

Research on financial markets explored the extent to which greater price transparency leads to higher market efficiency and liquidity (Granados et al. 2008). Multiple price information includes transaction price, price quotes and so on (i.e. bids or asks) (Bloomfield and O'Hara 1999; Granados et al. 2006; Soh et al. 2006). The effect of price information transparency is debatable based on the extant research. Theoretical research suggests that market transparency should matter, whereas the empirical evidence shows mixed findings (Bloomfield and O'Hara 1999). For instance, Flood et al. (1999) demonstrated that price transparency reduces opening spreads and increases trading volume based on their experimental markets, whereas Bloomfield and O'Hara's (1999) experiment drew contrary results. In addition, restricting the transparency debate to a certain type of price information, such as trade or quote, Pagano and Röell (1996) explored its different effects on different types of markets, such as auctions and dealer markets. The introduction of quote transparency in particular is considered to enhance the complexity of information transparency research. As Bloomfield and O'Hara (1999) indicated, the contrasting conjectures surrounding the benefits of quote transparency emphasize the general lack of knowledge of the effects of transparency on market behavior.

In prediction markets, there are informed and uninformed traders (Plott 2000). Markets are efficient, because information can be disseminated from the informed to the uninformed. This process is referred to as information aggregation (Gruca et al. 2005; Plott and Sunder 1982; 1988).

Information aggregation is processed through traders' trading activities. Quote information, one type of pre-trade information, shows a trader's individual bids and asks on a contract and represents the trader's expected value of the contract. Similarly, a transaction on a contract represents the aggregate expected value of the contract. These orders and transactions, in turn, become public information available in the market and other traders learn from it. Gradually, with an increased number of trades, information about a future event is disseminated from the informed to the uninformed.

Prior research on information transparency has suggested that information transparency in a market does not benefit everyone equally. Zhu (2002) argued that participants with different positions in the market have different incentives when they can see each other's bid or ask information. In a B2B market, transparent information about buy and sell orders benefits low-cost suppliers and high willingness-to-pay buyers due to the exposure of their competitive costs and purchase prices, respectively. Conversely, high-cost suppliers and low willingness-to-pay buyers will not be motivated to participate in a market that exposes their unfavorable orders.

In a prediction market, incentives to participate differ according to each trader's private information, particularly when the total number of traders is very constrained. Informed traders are not likely to actively place buy or sell orders, as these orders will reveal their private information to other traders. When traders' participation activity is high, informed traders would be willing to participate, as they expect to observe different private information from other informed traders. However, when traders' participation activity is low, informed traders will anticipate a smaller possibility that private information exists in the market. In turn, informed traders are inclined to withhold their buy or sell orders. Uninformed traders, contrarily, are willing to place buy or sell orders. Their orders can help them discover if any informed traders and private information exists in the market. For example, an uninformed trader places a buy order arbitrarily. If a transaction is successfully made, it probably means that someone else in the market does not expect a higher value of this contract. Alternatively, if no transaction occurs or the subsequent sell order is at a higher price, the uniformed trader will learn that other traders expect a higher value of this contract. Nevertheless, uninformed traders may not participate actively in a thin internal prediction market. Our explorative case study suggests that employees participate in an internal prediction market whenever they have relevant or updated information about future events.

As a result, in a thin internal prediction market, the revelation of price information will hinder the trader's participation activity. In turn, we construct the following hypothesis (H_{1a}):

H_{1a}: When an internal prediction market has only a few actively participating traders, disclosure of price information leads to a lower level of traders' activity.

Traders are sensitive to the prices of contracts, as prices are the signals they learn from to constantly update their beliefs (Gruca et al. 2005; Rhode and Strumpf 2004). Prices persistently carry information from those with more to those with less information in a market (Spence 2002). In a prediction market, quote information can be referred to as market signals, because they are the activities of individuals in a market, which by design or accident alter the beliefs of, or convey information to other individuals in the market (Spence 1974).

Traders in a prediction market are motivated to deal with signals, as information is initially asymmetric and is transmitted via signals. In order to observe the information that other traders have, a trader, as a signal receiver would refer to the signal (such as other traders' bids and asks) and respond accordingly. The response is embodied by the receiver's adjustment of his or her expected value of a contract in the same direction with the signaler. Additionally, the adjustments of quotes yields updated information by which other traders learn, and therefore, leads to further revisions on the expectations of contracts. Hence, one trader's revision of buy or sell orders on contracts is not only the consequence of learning, but also the cause of another trader's revision. Chen et al. (2009) referred to this as trader's dynamic interactions.

In an internal prediction market with constrained traders, informed traders are not likely to actively update their opinion of future events, as their adjustment of an order on a contract implies the improvement of their estimation. Other traders may realize this improvement and learn from it, forming a similar opinion. Traders in a market in fact trade on difference rather than similarity. Surowiecki (2004) argued that traders are motivated to act from disagreement and contest rather than consensus or compromise. If everyone holds a similar opinion, it is impossible to make profit from a trade, and thus, trades would no longer exist. When individual adjustment is limited, the influence of one trader's information update on another trader's opinion becomes even more constrained. Accordingly, we establish hypothesis (H_{2a}) as follows:

H_{2a}: When an internal prediction market has only a few actively participating traders, disclosure of price information leads to a decrease in traders' dynamic interactions.

5.2.2 Traders' Behavior and Market Information Aggregation Efficiency

Information aggregation is the process of information dissemination from "insiders" to "outsiders" (Plott and Sunder 1982; 1988; Gruca et al. 2005). In turn, traders' beliefs regarding the potential outcomes of a future event in a prediction market become convergent. Wolfers and Sitzewitz (2006a) and Gjerstad (2004) demonstrated that when traders' beliefs are convergent, the market price in stock markets will be very close to the mean of market participants' beliefs. In turn, information aggregation efficiency of a prediction market refers to the ability of the market to synthesize the traders' mean belief. The deviation of transaction prices from this mean belief indicates information aggregation efficiency: the smaller the deviation, the more efficiently the market aggregates the traders' consensus.

The mean of traders' beliefs can be represented by an equilibrium price. From a microeconomic point of view, the equilibrium price can be identified as the price at which the quantity of a demanded contract equals the quantity supplied. The prices of bids and asks correspond to the trader's perceived value of the contract, representing the possible outcome of a future event. Hence, this value is determined by the trader's estimation of the possibility of the event. Thus, the resulting equilibrium price represents a mean of individuals' probability estimations, and the resulting market price in prediction markets could predict the possibility of future events when it is strongly correlated with the equilibrium price.

However, in an information asymmetric market, transaction prices of a contract are often above or below the average of reservation prices depending on the elasticity of the demand or supply curve. It then becomes extremely difficult to achieve the equilibrium price. However the price formation mechanism of a double auction allows traders to observe other individuals' beliefs based on the quote or transaction prices, and then to incorporate that information into their own expectations. With these new expectations come new demand functions and, therefore, new prices (Hahn and Tetlock 2006). Each trading activity in fact aggregates information into the market. If all the information is revealed in the price and information aggregation is efficient, eventually the equilibrium price can be achieved. Accordingly, it is important to stimulate traders to actively participate in a prediction market.

The following hypothesis (H_3) is suggested:

H_3: An increased level of traders' participation activity in a prediction market leads to higher information aggregation efficiency.

In a prediction market, payoffs are tied to the individual trader's predictive accuracy of the future event and thus trading profit or loss is straightforward. Traders are, therefore, motivated not only to truthfully incorporate their private information and any other relevant information into trading decisions, but also to seek information about the future event (Berg and Rietz 2003; Oliven and Rietz 2004; Wolfers and Zitzewitz 2004). Consequently, prediction markets have the ability to aggregate information from individuals, who filter both public and private information, and weigh this information through the price formation process (Berg and Rietz 2003).

Traders learn and keep updating their beliefs based on different newly-acquired information. This learning process is reflected in their ever-changing buy and sell orders (Gruca et al. 2005; Rhode and Strumpf 2004). Besides non-market information, such as media news of a future event, traders learn from others' expected values of contracts inside a market. Traders iteratively learn and adjust their individual expectations. As a result, their expectations will eventually converge and trade will cease in the market (Davis and Holt 1993). Until then, the convergent expectation should have captured all of the information for the estimation of the future event. In other words, the traders' mean belief should have been captured and reflected in the transaction price of a contract in a prediction market. Thus, the deviation between the transaction price and the equilibrium price of a contract, which represents the traders' mean belief, is reduced. Consequently, traders' dynamic interactions, in addition to traders' participation activity, affect the process of information aggregation. Therefore, we propose hypothesis (H_4) as follows:

H_4: An increase in traders' dynamic interactions in a prediction market leads to higher information aggregation efficiency.

5.2.3 Information Aggregation Efficiency and Market Predictive Accuracy

The theoretical foundation of prediction markets, the rational expectations hypothesis (Muth 1961) and the efficient market hypothesis (Fama 1970) suggested that higher information aggregation efficiency leads to more accurate market prediction. Previous studies on prediction markets also demonstrated that the market can accurately predict future events by efficiently aggregating dispersed information (such as Gadanecz 2007; Gruca et al. 2005; Plott

2000). Essentially, these theories proposed that a prediction market can forecast accurately due to its robust ability to aggregate information. In accordance with these arguments, we construct the hypothesis (H_5) as follows:

H_5: Higher information aggregation efficiency of a prediction market leads to higher market predictive accuracy.

5.3 RESEARCH METHODS

In this section, we describe the details of the laboratory experiment, including the experiment design, the market design, contracts, subjects, incentives and experiment procedures.

5.3.1 Laboratory Experimental Design

With regard to information transparency, this dissertation focuses on price transparency, particularly quote information in prediction markets, as this pre-trade information is likely to influence traders' behavior. We identified two conditions of price information in this study. One is "opaque", in which traders do not see others' buy or sell orders, neither the price nor the number of shares. The other condition is "transparent", in which traders see the highest outstanding buy order and the lowest outstanding sell order, including the price and the total number of shares.

In these laboratory experiments, we adopted a within-subjects design. Every subject took part in two markets and each market corresponded to a specific transparency condition of price information. The major advantage of a within-subjects design is the control for differences across cohorts (Bloomfield and O'Hara 1999). Subjects may differ according to characteristics, such as intelligence, personality, motivation or familiarity with the experimental environment (Davis and Holt 1993; Kagel and Roth 1995). Such variations between subjects can make it difficult to draw inferences about the effect of price information transparency levels if one cohort of subjects participate in one setting and another cohort participates in another, because the effect of the treatment might actually reflect differences in the cohorts' characteristics (Bloomfield and O'Hara 1999). Therefore, to avoid this potential confounding issue, we let each cohort of subjects trade in both transparency settings.

However, a within-subjects design also entails the disadvantage of order effects, such as learning and fatigue. Due to the complexity of laboratory markets, even the same subjects may behave differently in the later repetitions of tasks than in early repetitions (Forsythe and Lundholm 1990). Bloomfield and O'Hara (1999) emphasized the importance of not running different settings in a fixed sequence, as any apparent differences may actually be due to subject's learning or fatigue rather than to the different treatments. Consequently, we followed the principle of a balanced Latin square design (Field and Hole 2003) to order the experimental market sequences: one cohort of the subjects participated in the opaque market first and then the transparent market, and the subsequent cohort participated in the transparent market first and then the opaque market.

Furthermore, according to our pilot studies of four cohorts (including a total of 20 subjects), training was crucial to familiarize subjects with the trading tasks, as almost none of the subjects had experiences with prediction markets. Consequently, each cohort of subjects was required to participate in three markets, including the first trial market for training. The transparency condition used in this first market was identical to the condition in the last market. Table 5.1 illustrates the order of the experimental market sequences for each cohort of subjects.

To engage with practitioners in our research and design the prediction markets to mirror the implementations in real business contexts, we conducted the laboratory experiments in collaboration with TaoBao (www.taobao.com), a leading online B2B2C market with approximately 500 million registered users in China (by 2011). TaoBao provided us with its actual business events for prediction and the data for contract design.

Table 5.1 Order of Experimental Market Sequences

Cohort Number	*Training Market*	*First Market*	*Second Market*
1	Transparent	Opaque	Transparent
2	Opaque	Transparent	Opaque
⋮	⋮	⋮	⋮
21	Transparent	Opaque	Transparent
22	Opaque	Transparent	Opaque

5.3.2 Market Mechanism Design

A web-based continuous double auction mechanism was used in the laboratory experiments. On a single web page, all of the contracts for a market were available. Due to the different price information conditions, the web pages for each setting were slightly different. However, the fundamental design was similar and developed based on the one used in the previous explorative case study.

Figure 5.1a and 5.2a illustrate the market of opaque and transparent price information conditions. At the top of the web page, the future event being predicted was displayed. Beneath it was the trading part, in which all the contracts were listed in the column "stocks". Historic prices of contracts were exhibited as a line chart. An overview of the trader's buy and sell orders was provided in the bottom, showing the status of an order, namely executed or not. In the opaque market, the columns including lowest sell and highest buy were not presented, although they were displayed in the transparent market.

At the beginning of each market, every trader received an endowment, including 1,000 points of play money and 10 shares per contract.

5.3.3 Contracts Design

All of the markets in the laboratory experiments predicted the annual sales of a certain category of products or services sold on www.taobao.com in 2008. In total, there were 43 categories, such as computer and networking, women's clothing, and gift cards. The prediction events were randomly assigned to each market, with no repetition within a single session, in which a cohort of subjects participated in three different markets. Every market had five contracts, representing the five possible ranges of sales of a certain product or service category up for prediction. The contracts were co-designed with TaoBao, and one of the five contracts corresponded to the actual sales result. Table 5.2 summarizes the 43 product or service categories being predicted and their corresponding contracts.

To illustrate a market, we take the product category "Flowers and Cakes" as an example. In this market, the event to be predicted was the annual sales of flowers and cakes on www.taobao.com in 2008 in RMB. Contract "238-240" represented that the sales of this product category on www.taobao.com in 2008 fell between 238 million RMB and 240 million RMB.

In the experiments, every subject received a piece of private information in each market, indicating which specific contract was definitely not the actual sales outcome. However, none of the subjects were informed about which contract represented the actual sales.

According to Taobao, the data they provided to us were never revealed to the public or used in any other research activities outside Taobao. This situation ensured that none of the subjects in the experimental markets were informed traders, avoiding information asymmetry among the traders. Additionally, Taobao masked the original data before they delivered it to us.

5.3.4 Subjects

The subjects in these laboratory experiments were students of Erasmus University. Student subjects are viewed as the standard subject pool used by experimenters (Harrison and List 2004). We advertised our laboratory study to the subject pool of the university behavioral lab via its official website. A total of 132 university students were recruited and randomly assigned to 22 cohorts, thus, 6 subjects per cohort. Each cohort was invited to a computer lab in sequence. A session encompassed all of the tasks that a cohort must complete in the experiment. Every subject was informed about his or her session time and was required to confirm in advance. Three days and one day prior to the scheduled time, a reminder was sent to the subjects by email in order to reduce the no-show rate.

5.3.5 Incentives

Three different types of cash rewards were offered to the subjects. The first type was an "attendance reward". A subject who participated and completed the entire session received this basic reward of 10 euros. The other two additional rewards were offered based on the subject's individual performance. In each market, a subject received an additional 0.50 euros per share of the contract owned which represented actual sales. (This included only shares that were in addition to the 10 shares in the endowment.) This type of reward was termed a "prediction reward" and was developed to motivate subjects to learn in the market. The last type of reward was a "trading reward". In each market, the subject who had the most play money in their account at the end of the experiment earned an additional 2.00 euros. The trading reward was designed to motivate subjects to trade actively in the prediction market. Subjects were informed that they would not be eligible for the market rewards if they did not place buy or sell orders in that market.

Figure 5.1a Screenshot of an Opaque Market with No Quote Information in Laboratory Experiments

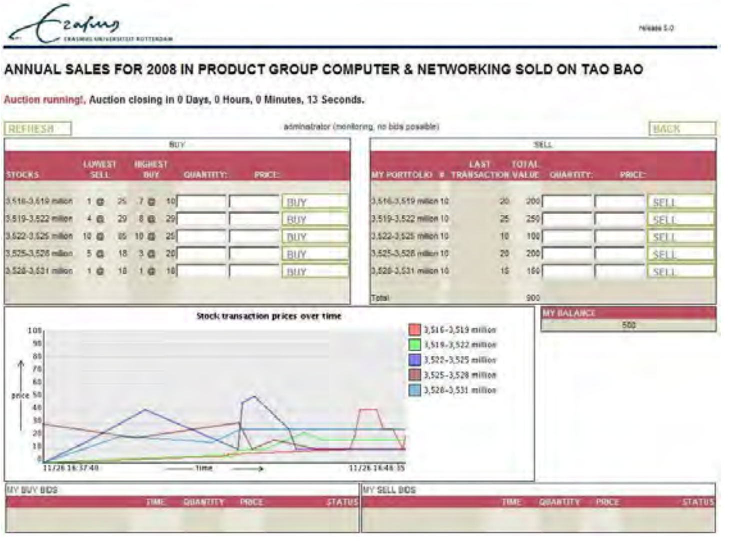

Figure 5.1b Screenshot of a Transparent Market with Quote Information in Laboratory Experiments

Table 5.2 Product Categories and Contracts

Product Category	*Contract 1 (¥[1] million)*	*Contract 2 (¥ million)*	*Contract 3 (¥ million)*	*Contract 4 (¥ million)*	*Contract 5 (¥ million)*
Adult Supplies	313-315	315-317	317-319	319-321	321-323
Antiques	1,359-1,362	1,362-1,365	1,365-1,368	1,368-1,371	1,371-1,374
Baby	2,507-2,510	2,510-2,513	2,513-2,516	2,516-2,519	2,519-2,522
Beauty & Massage	1,125-1,128	1,128-1,131	1,131-1,134	1,134-1,137	1,137-1,140
Beds	894-896	896-898	898-900	900-902	902-904
Books	1,177-1,180	1,180-1,183	1,183-1,186	1,186-1,189	1,189-1,192
Cameras & Photo	2,469-2,472	2,472-2,475	2,475-2,478	2,478-2,481	2,481-2,484
Cars	1,896-1,899	1,899-1,902	1,902-1,903	1,903-1,906	1,906-1,909
Children's Clothing	1,079-1,082	1,082-1,085	1,085-1,088	1,088-1,091	1,091-1,094
Computers & Networking	3,516-3,519	3,519-3,522	3,522-3,525	3,525-3,528	3,528-3,531
Cosmetics/Perfumes	5,690-5,693	5,693-5,696	5,696-5,699	5,699-5,702	5,702-5,705
Dolls & Bears	1,220-1,223	1,223-1,226	1,226-1,229	1,229-1,232	1,232-1,235
Electrics	2,123-2,126	2,126-2,129	2,129-2,132	2,132-2,135	2,135-2,138
Fashionable Accessories	1,423-1,426	1,426-1,429	1,429-1,432	1,432-1,435	1,435-1,438
Female Clothing	7,911-7,914	7,914-7,917	7,917-7,920	7,920-7,923	7,923-7,926
Female Shoes	1,726-1,729	1,729-1,732	1,732-1,735	1,735-1,738	1,738-1,741
Flowers & Cakes	238-240	240-242	242-244	244-246	246-248
Food	2,036-2,039	2,039-2,042	2,042-2,045	2,045-2,048	2,048-2,051
Furniture	898-900	900-902	902-904	904-906	906-908
Gift Cards	646-648	648-650	650-652	652-654	654-656
Health	1,711-1,714	1,714-1,717	1,717-1,720	1,720-1,723	1,723-1,726
Home	1,876-1,879	1,879-1,882	1,882-1,885	1,885-1,888	1,888-1,891
Household Appliances	2,954-2,957	2,957-2,960	2,960-2,963	2,963-2,966	2,966-2,969
Internet Phones	1,595-1,598	1,598-1,601	1,601-1,604	1,604-1,607	1,607-1,610
Lamps & Hardware	1,444-1,447	1,447-1,450	1,450-1,453	1,453-1,456	1,456-1,459
Laptops	3,441-3,444	3,444-3,447	3,447-3,450	3,450-3,453	3,453-3,456
Logistical Service	383-385	385-387	387-389	389-391	391-393
Male Clothing	2,885-2,888	2,888-2,891	2,891-2,894	2,894-2,897	2,897-2,900

[1] "¥" is the symbol of RMB, Chinese currency. In 2008, 1.00 euro equals approximately to 10.00 RMB.

Memory Cards & USB	512-514	514-516	516-518	518-520	520-522
Mobile Phones	7,823-7,826	7,826-7,829	7,829-7,832	7,832-7,835	7,835-7,838
Mobile Phone Prepaid Cards	1,358-1,361	1,361-1,364	1,364-1,367	1,367-1,370	1,370-1,373
MP3/iPod	982-984	984-986	986-988	988-990	990-992
Music	562-564	564-566	566-568	568-570	570-572
Office Supplies	1,360-1,363	1,363-1,366	1,366-1,369	1,369-1,372	1,372-1,375
Online Games	9,732-9,735	9,735-9,738	9,738-9,741	9,741-9,744	9,744-9,747
Outdoor Sports	785-787	787-789	789-791	791-793	793-795
Pet Supplies	591-593	593-595	595-597	597-599	599-601
Software	1,232-1,235	1,235-1,238	1,238-1,241	1,241-1,244	1,244-1,247
Travel	513-517	515-517	517-519	519-521	521-523
Underware	1,201-1,204	1,204-1,207	1,207-1,210	1,210-1,213	1,213-1,216
Video Games	75-77	77-79	79-81	81-83	83-85
Watches	1,314-1,317	1,317-1,320	1,320-1,323	1,323-1,326	1,326-1,329
ZIPPO & Swiss Army Knife	5,942-5,945	5,945-5,948	5,948-5,951	5,951-5,954	5,954-5,957

5.3.6 Experimental Procedures

The duration of a complete session with a cohort was approximately 90 minutes and consisted of three parts. Subjects in a session first gathered in a waiting room in the lab. Instructions, printed on one A4 paper (see Appendix II), were offered and the experiment administrator gave supplementary instructions orally. The instructions briefly introduced the major tasks the subjects would do, the reward scheme, and other important details that subjects should pay attention to. At the end of the instruction period, the subjects were allowed to raise any questions or ask for clarification. This part usually took no longer than 10 minutes.

Subsequently, subjects were led to a lab with individual computer cubical rooms and the second part of the session commenced. Each cubical room was furnished with headphones connected to the lab's internal communication system, a pen, writing paper and the necessary documents for the ensuing prediction markets. The experiment administrator used the lab's internal communication system to transmitted instructions to the subjects. Subjects were required to participate in three sequential prediction markets. Before the beginning of each market, subjects were given three minutes to read the information given to them about that market (see Appendix III). The information included private information and general historical sales information about the specific category of products or services. The duration of each market was exactly 10 minutes. After each market, subjects were asked to complete a small survey regarding their use of information in the preceding market (see Appendix IV). During this part, the administrator instructed the subjects when to read the information and fill in the questionnaire and announced the opening and closing of each market through the internal communication system.

Finally, after trading in the three markets was complete, subjects were required to leave everything inside their cubicles and return to the waiting room, where a debriefing was held. In the debriefing, the administrator first announced if all the subjects were eligible for the reward and then announced the winners of the prediction reward and the trading reward in each market, including the total amount of cash each subject would obtain. Afterwards, the cash rewards were distributed to every subject.

5.4 MEASURES

As the research model of the laboratory experiments shows, the measures involve three variables, namely traders' participation activity, traders' dynamic interactions and market predictive accuracy. The measures of the former two variables are identical to the measures of the same variables in Chapter 4 (see 4.4 Measures). To recap, the measure of traders' participation activity includes the contract level (i.e. number of transactions and number of shares traded) and the individual trader level (i.e. number of buy orders/sell orders and number of shares in buy orders/sell orders). Similarly, the measure of traders' dynamic interaction entails the contract level (i.e. 1-influential, 2-influential, 3-influential, and 2out3-influential orders) and the individual trader level (i.e. Type I and Type II self-revisions).

5.4.1 Measure of Information Aggregation Efficiency

According to current research, there are two ways of measuring information aggregation efficiency, nevertheless, neither fulfilled the needs of this study. One measurement compares the transaction prices with the competitive equilibrium price of a contract; the competitive equilibrium price corresponds to the reward, given that all private information is aggregated and reflected in the market. Therefore, the smaller the difference between the transaction price and the competitive equilibrium price of a contract, the higher the information aggregation efficiency (See Plott 2000). However, this measurement is used in laboratory experiments, where the certainty of private information is ensured and the actual result is known. While the measurement shows the robust ability of prediction markets to aggregate information, it cannot be used in a real business environment, where the certainty and the availability of private information are not ensured and the outcome of the future event is unknown.

The other measurement compares traders' average estimation of a future event prior to market opening with the actual result. The closer the two results, the more efficient the information aggregation (see Gruca et al. 2005). A prediction market forecast reflects the market consensus and traders' average estimation represents consensus. The comparison between these two measurements, therefore, indicates to what extent the market captures the traders' consensus. However, this method neglects the fact that information aggregation is a process, in which traders keep learning while trading and bring new information into the market (Bondarenko and Bossaerts 2000; Gruca et al. 2005; Ho and Chen 2007; Rhode and Strumpf 2004). In turn, traders' average estimation of the future event prior to the market opening does not actually imply their consensus after learning. Alternatively, we can collect the traders' average estimation of the future event in the end of the market, after learning in the market. Nonetheless, in reality, it is not ensured that all traders, or at least most of the traders, will submit their personal estimate. Additionally, existing traders may leave and new traders may come to a market. Furthermore, it is impossible to measure the information aggregation efficiency until the end of the market.

The measurement we develop in this study is based on the comparison between the transaction price and the dynamic equilibrium price of a contract. A trader's buy and sell order of a contract corresponds to his or her perception of the possibility of an outcome of a future event. When there is no difference between traders' perceived value of a contract, no shares are traded further. A demand curve of a contract can be extracted based on all the buy orders of this contract, and a supply curve can be drawn based on all the sell orders of the contract. An equilibrium price is identified as the price at which the quantity of a demanded contract equals the quantity supplied and in the absence of external influences the equilibrium value will not change. The equilibrium price of a contract, based on the demand and supply curve of the contract, thus, represents the market consensus on the probability estimation of the corresponding outcome. This equilibrium price of the contract evolves along with each trader's learning and the development of the market. This is referred to as the dynamic equilibrium price. This measurement is illuminated by the study of Martin (2006).

To be specific, our measurement entails the following four steps:

Step 1: Estimate the general equation for a linear demand curve

With regard to a contract in a prediction market, we plot the buy orders on two coordinate axes with reservation price on the vertical axis and quantity demanded on the horizontal axis. Reservation price refers to the price submitted in a buy order, and quantity refers to the total number of shares submitted in the buy orders with the same reservation price. A linear demand curve can be drawn and represented by the following equation:

$$Pd_i = a - b \times Qd_i \text{……………………….(4)}$$

where *i* represents a contract in a prediction market, Pd_i denotes the price demanded of the contract *i* and Qd_i denotes the quantity demanded. Mathematically, a is the vertical axis intercept and $-b$ is the slope. Economically, if price goes as high as a TB, traders will demand zero shares of contract *i*; b is the rate at which the price must fall for the quantity demanded to increase by one share. In turn, a must be positive, and the minus sign on b indicates that quantity demanded and price are inversely related.

Step 2: Estimate the general equation for a linear supply curve

Similar to *Step 1*, we plot the sell orders on two coordinate axes with reservation price on the vertical axis and quantity supplied on the horizontal axis. Reservation price refers to the price submitted in a sell order; and quantity refers to the total number of shares submitted in sell orders with the same reservation price. A linear supply curve can be drawn and represented by the following equation:

$$Ps_i = c - d \times Qs_i \text{……………………….(5)}$$

where *i* represents a contract in a prediction market, Ps_i denotes the price supplied of the contract *i* and Qs_i denotes the quantity supplied. Mathematically, c is the vertical axis intercept of the supply curve and d is its slope. Economically, traders will offer zero shares for sale if the price drops as low as c TB, and d is the rate at which the price must rise for traders to offer one more share for sale. Thus, the intercept c is positive, and the positive sign on d indicates a direct relationship between price and quantity supplied.

Step 3: Calculate the dynamic equilibrium price of a contract

To find the equilibrium price, we apply the condition that quantity demanded equals quantity supplied: $Qd_i = Qs_i = Qe_i$, where Qe_i denotes the equilibrium quantity of contract *i*. Substituting Qe_i into the demand and supply equations and noting that there is just one equilibrium price, we can set the two equations equal to each other: $a - b \times Qd_i = c - d \times Qs_i$. Accordingly, we obtain the result: $Qe_i = \frac{a-c}{b+d}$. By inserting this value for the equilibrium quantity into either the demand or supply equation of contract *i*, we can determine that the equilibrium price is as follows:

$$Pe_i = \frac{ad+bc}{b+d} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(6)$$

where Pe_i denotes the dynamic equilibrium price of contract *i*. Since *a*, *b*, *c* and *d* are all positive, Pe_i is also positive.

Step 4: Calculate the average percentage deviation of the transaction price from the dynamic equilibrium price of contracts in a market

To compare information aggregation efficiency between different prediction markets, we finally calculate the average percentage deviation of the transaction price from the dynamic equilibrium price of contracts in a market as follows:

$$\frac{\sum_i^n |(P_i - Pe_i)/Pe_i|}{n} \times 100\%$$

where P_i is the transaction price of contract *i* and n is the number of contracts in a prediction market. The smaller the average percentage deviation of the transaction price from the dynamic equilibrium price, the higher the information aggregation efficiency in a prediction market.

5.4.2 Measure of Market Predictive Accuracy

With regard to market predictive accuracy, we examine how accurately a market predicts future events. Market predictive accuracy is usually assessed against two benchmarks, including the actual sales results and the estimation generated from the competing forecasting mechanism. The accuracy assessed against the former criterion is referred to as the absolute accuracy; the accuracy assessed against the latter criterion is referred to as relative accuracy (Berg and Rietz 2003). Given that it is generally more difficult to achieve absolute accuracy, more emphasis is put on relative accuracy. This decision fulfills the need of most companies, which aim to find an improved forecasting mechanism compared to existing mechanisms. Nevertheless, as the actual results of sales of the product or service categories in 2008 on www.taobao.com are available to us, the experiments assess absolute accuracy. In other words, we measure the market predictive accuracy based on the comparison of market prediction and actual sales. The smaller the difference between these two figures, the more accurate the market prediction.

The measure of market predictive accuracy in laboratory experiments follows prior research on internal prediction markets in HP (Plott and Chen 2002), which were among the first internal prediction markets. We follow the measurement of this prior research for four primary reasons. First, the future events being predicted in HP markets were sales of HP products, similar to the experimental markets in this study. Second, the contract design in HP markets was similar to our study. In both studies, each contract represents a possible range of sales. Third, Plott and Chen (2002) identified the measurement of the point estimation of the market prediction. This point estimation allows researchers to calculate the absolute difference between the market prediction and actual sales, precisely comparing the two figures. Last, Plott and Chen (2002) further illustrated the particular measurement of market predictive accuracy, namely, the percentage error, based on the aforementioned comparison. To be specific, this measure entails the following three steps.

Step 1: Use price to measure the likelihood of a contract

In a prediction market, the transaction price of a contract indicates trader's agreed opinion of the contract. The higher the price, the more likely the outcome presented by the contact (in the estimation of the traders). However, a price is not a probability; it is a positive real number. To use a price to measure the likelihood of the outcome presented by a contract, we construct the following measurement:

$$Pr_i = \frac{P_i}{\sum_i P_i} \text{.......................(1)}$$

where *i* represents a contract in a prediction market and Pr_i denotes the probability that the contract *i* would happen. The construction of Pr_i determines that its value is between [0, 1]. This construct also ensures that the higher the price P_i, the higher the corresponding probability. The summation of Pr_i is $\sum_i Pr_i = 1$.

Different prices can be taken into consideration, such as the last transaction price of a contract, the average price, or the weighted average price of a contract during a certain time period. In this study, we consider the last transaction price and the weighted average price of a contract. Usually, the last transaction price is expected to reflect the most accurate information about future events. However, due to the very limited operation time (10 minutes) of each market in our laboratory experiments, the weighted average transaction price of contracts could be more representative of the information. As there are few existing studies, we do not know which price may generate a more accurate market prediction in this case. Thereby, we take both prices into our calculation.

Step 2: Estimate a market prediction

Suppose the outcome represented by contract *i* will definitely happen, the market prediction would be

$$Sale_{market} = M_i \cdot Pr_i = M_i \cdot 1 = M_i \ldots\ldots\ldots\ldots\ldots\ldots\ldots..(2)$$

where M_i denotes the mid-point of the numerical range represented by contract *i*. For instance, "238-240" is one of the contracts of the market that predicts the annual sales of product category "Flowers and Cakes" on www.taobao.com in 2008. The mid-point of this contract is thus "239". Following the rationale of Plott and Chen (2002), since there is no specific information within a range of numbers represented by the contract and all the ranges are finite, a uniform distribution is adopted. The mid-point of a range is regarded as the expectation of a uniform distribution.

In reality, we are uncertain of the probability of a contract. Nonetheless, we know the probability of each contract in a market, and therefore, the market prediction becomes a weighted average of all the contracts and the weight is the probability of occurrence. In turn, we construct the formula for the point estimation of market prediction, namely, the sales result forecasted by the market in the experiments, as follows:

$$\mathrm{Sale}_{\mathrm{market}} = \sum_i Pr_i \cdot M_i \ldots\ldots\ldots\ldots\ldots\ldots\ldots..(3)$$

Step 3: *Calculate the percentage error*
We finally calculate the percentage error of a market prediction against the actual result of the event being predicted as follows:

$$\%\ \mathrm{Error} = \frac{|\mathrm{Sale}_{\mathrm{actual}} - \mathrm{Sale}_{\mathrm{market}}|}{\mathrm{Sale}_{\mathrm{actual}}} \times 100\%$$

where $Sale_{actual}$ denotes the actual annual sales of a product or service category on www.taobao.com in 2008. $Sale_{market}$ denotes the market point estimation of the sales. The difference between the market prediction and the actual result specifically means the absolute value of the difference. The smaller the percentage error, the higher the predictive accuracy of the market.

5.5 RESULTS

This section discusses the results of the laboratory experiment and validates the hypotheses based on these results. We first present the overview of the subjects' participation in the experiments. Thereafter, we delineate the results according to the sequence of the hypotheses.

5.5.1 Overview of Subjects' Participation

As mentioned in the research design of this chapter, we invited 132 subjects to participate in the laboratory experiments based on 6 subjects per session and 22 sessions in total. However, 23 subjects were absent on short notice and replacements could not be arranged in time. Consequently, 109 subjects participated in the experiments. Table 5.3 exhibits the participation of subjects in the experimental markets. As this table shows, not every session had 6 subjects as 23 subjects were absent. Thus, the market size varied: three sessions had only three subjects; three sessions had four subjects; eight sessions had five subjects; and eight sessions had six subjects.

Table 5.3 Overview of Subjects' Participation in the Experimental Markets

Market size	*Number of opaque markets*	*Number of transparent markets*
3 subjects	3	3
4 subjects	3	3
5 subjects	8	8
6 subjects	8	8

As described in the experimental procedures, every subject participated in three markets. Since the first market was designed to familiarize subjects with the experimental tasks and system operations, the data generated from this training market was not included in the following data analyses. Therefore, a total of 88 markets were counted for the statistical analyses.

Furthermore, it should be clarified that due to the different number of subjects in each market, we adopted the weighted number of each indicator, whenever the analysis is on a contract level. To be specific, we adjusted the measurement by weighting numerical values by the ratio of traders, 3/6 = 0.5, for markets with three subjects; 4/6 =0.667, for markets with four subjects; 5/6=0.833, for markets with five subjects.

Moreover, all 109 subjects completed a full session, including one training market, one opaque market, one transparent market, and the follow-up questionnaire for each market, and were active traders in every market. Therefore, all of them were included in the analyses.

5.5.2 Effects of Information Transparency on Trader's Participation Activity

Table 5.4 summarizes the statistics for the average trader's participation activity at the contract level in the opaque and transparent markets. We use the Roman numerals to indicate the markets: upper-case numbers represent opaque markets and lower-case numbers represent transparent markets.

A Mann-Whitney test based on the 110 contracts in each type of market further manifested that the difference between the number of transactions per contract in opaque and transparent markets was significant ($U(110) = 5103$, $z = -2.01$, $p < 0.045$). As Table 5.4 exhibits, approximately 20% more transactions occurred in opaque markets than in transparent markets ($Mean_{opaque} = 16$, $Mean_{tansparent} = 13$).

However, the number of shares traded per contract in the two types of markets did not differ ($U(110) = 5941$, $z = -0.23$, $p > 0.81$). According to Table 5.4, the average number of shares traded per contract was similar in both types of markets ($Mean_{opaque} = 67$, $Mean_{tansparent} = 68$); the difference is as small as 1.5%. The possible reason is that traders do not determine the number of shares in their buy and sell orders based on the revelation of price information. Transactions are traders' matched buy and sell orders. Therefore, the shares traded do not differ significantly according to the disclosure of price information. In fact, the following analyses at the trader level support this explanation.

Table 5.5 shows the statistics for the average trader's participation activity at the trader level in each market. A Wilcoxon test was performed to further compare the corresponding measures across the two markets with different information transparency. The results showed that there was a significant effect of price transparency on trader's participation activity based on the measure of number of buy orders ($W(109) = 1633$, $z = -3.20$, $p < 0.01$) and number of sell orders ($W(109) = 1706$, $z = -2.95$, $p < 0.01$). Table 5.5 further illustrates that there were 27% more buy orders ($Mean_{opaque} = 14$, $Mean_{tansparent} = 11$) and 30% more sell orders ($Mean_{opaque} = 17$, $Mean_{tansparent} = 13$) per trader in opaque markets than transparent markets.

The measures of the number of shares in buy orders ($W(109) = 2601$, $z = -1.20$, $p > 0.23$) and the number of shares in sell orders ($W(109) = 2434$, $z = -1.56$, $p > 0.11$) did not exhibit this significant effect, even though the difference of the number of shares in buy orders ($Mean_{opaque} = 135$, $Mean_{tansparent} = 98$) and the number of shares in sell orders ($Mean_{opaque} = 126$, $Mean_{tansparent} = 104$) between the two types of markets seemed to be large. As discussed above, a possible reason is that traders do not determine the number of shares in their buy and sell orders based on the revelation of price information but their estimation of the corresponding probability of the contracts. When a trader is more certain about the probability of the outcome represented by the contract, the trader is likely to buy or sell the contract in a large quantity at a certain price, and vice versa. In this experimental study, every trader was informed about a piece of accurate information about future events. Therefore, the numbers of shares in buy and sell orders were not significantly different.

Table 5.4 Summary Statistics for Traders' Participation Activity at the Contract Level

Opaque market	*Transparent market*	*Weighted number of transactions*		*Weighted number of shares traded*	
I	i	8	(7)	33	(36)
II	ii	19	(13)	45	(32)
III	iii	24	(21)	92	(115)
IV	iv	8	(6)	12	(20)
V	v	15	(14)	45	(92)
VI	vi	27	(14)	59	(42)
VII	vii	5	(5)	48	(48)
VIII	viii	9	(7)	83	(49)
IX	ix	15	(16)	88	(91)
X	x	29	(39)	153	(112)
XI	xi	2	(7)	7	(54)
XII	xii	16	(2)	28	(2)
XIII	xiii	18	(8)	112	(65)
XIV	xiv	12	(15)	119	(138)
XV	xv	17	(17)	53	(67)
XVI	xvi	7	(8)	51	(58)
XVII	xvii	25	(10)	89	(77)
XVIII	xviii	13	(14)	86	(102)
XIX	xix	25	(18)	65	(121)
XX	xx	16	(9)	74	(44)
XXI	xxi	25	(20)	87	(69)
XXII	xxii	8	(12)	48	(62)
Average		*16*	*(13)*	*67*	*(68)*

Note: Numbers in parentheses are from transparent markets.

Table 5.5 Summary Statistics for Traders' Participation Activity at the Trader Level

Opaque market	*Transparent market*	*Number of buy orders*		*Number of shares in buy orders*		*Number of sell orders*		*Number of shares in sell orders*	
I	i	6	(7)	25	(44)	11	(11)	67	(87)
II	ii	11	(13)	128	(133)	10	(5)	105	(62)
III	iii	11	(7)	27	(189)	13	(4)	40	(9)
IV	iv	15	(9)	145	(94)	22	(13)	199	(140)
V	v	3	(5)	52	(84)	4	(7)	21	(73)
VI	vi	12	(14)	210	(298)	14	(12)	159	(131)
VII	vii	13	(9)	37	(24)	18	(12)	79	(46)
VIII	viii	11	(5)	13	(27)	11	(7)	47	(25)
IX	ix	11	(9)	82	(55)	13	(13)	84	(88)
X	x	17	(22)	276	(83)	35	(40)	478	(143)
XI	xi	13	(6)	72	(141)	23	(10)	132	(114)
XII	xii	21	(12)	94	(99)	27	(17)	137	(176)
XIII	xiii	17	(13)	93	(57)	22	(15)	115	(86)
XIV	xiv	12	(9)	59	(48)	18	(12)	140	(79)
XV	xv	21	(18)	147	(157)	26	(35)	157	(332)
XVI	xvi	8	(9)	29	(99)	21	(15)	121	(127)
XVII	xvii	21	(11)	59	(34)	20	(14)	63	(55)
XVIII	xviii	26	(11	564	(110)	12	(11)	88	(94)
XIX	xix	9	(11	62	(46)	18	(12)	102	(52)
XX	xx	9	(8)	128	(94)	5	(8)	75	(95)
XXI	xxi	13	(13)	397	(159)	16	(16)	287	(242)
XXII	xxii	17	(11)	279	(81)	11	(7)	81	(39)
Average		*14*	*(11)*	*135*	*(98)*	*17*	*(13)*	*126*	*(104)*

Note: Numbers in parentheses are from transparent markets.

Therefore, it can be argued that when there are only a few actively participating traders in a prediction market, these traders tend to be less active in a transparent market than in an opaque market. In turn, the following hypothesis (H_{1a}) is supported.

H_{1a}: When an internal prediction market has only a few actively participating traders, disclosure of price information leads to a lower level of traders' activity.

5.5.3 Effects of Information Transparency on Trader's Dynamic Interaction

With regard to the trader's dynamic interactions, a Wilcoxon test was performed to analyze trader-level activity. The results indicated that there was a significant effect of information transparency on both Type I self-revisions ($W(109) = 1489$, $z = -4.03$, $p < 0.01$) and Type II self-revisions ($W(109) = 1688$, $z = -3.85$, $p < 0.01$).

Table 5.6 Summary Statistics for Traders' Dynamic Interactions at the Trader Level

Opaque market	*Transparent market*	*Number of Type I self-revisions*	*Number of Type II self-revisions*
I	i	10 (10)	10 (10)
II	ii	10 (10)	10 (9)
III	iii	14 (5)	13 (4)
IV	iv	21 (13)	21 (13)
V	v	2 (4)	2 (4)
VI	vi	12 (12)	12 (12)
VII	vii	81 (56)	18 (9)
VIII	viii	12 (5)	12 (5)
IX	ix	10 (8)	10 (8)
X	x	25 (23)	25 (23)
XI	xi	18 (7)	17 (6)
XII	xii	30 (14)	30 (14)
XIII	xiii	21 (14)	21 (14)
XIV	xiv	20 (12)	16 (11)
XV	xv	28 (30)	28 (30)
XVI	xvi	14 (14)	14 (14)
XVII	xvii	22 (12)	20 (12)
XVIII	xviii	23 (13)	22 (10)
XIX	xix	13 (11)	12 (11)
XX	xx	4 (5)	4 (5)
XXI	xxi	14 (15)	14 (14)
XXII	xxii	15 (8)	14 (8)
Average		*19 (14)*	*16 (11)*

Note: Numbers in parentheses are from the "transparent" markets.

The average number of self-revisions made by traders in each market (see Table 5.6) further revealed that there were approximately 36% more Type I self-revisions ($Mean_{opaque} = 19$,

$\text{Mean}_{\text{tansparent}} = 14$) and 45% more Type II self-revisions ($\text{Mean}_{\text{opaque}} = 16$, $\text{Mean}_{\text{tansparent}} = 11$) in an opaque market than in a transparent market. This implied that in opaque markets, traders are inclined to make more significant revision of their orders.

At the contract level, the analyses focused on the weighted number of four different types of influential orders. A Mann-Whitney test revealed a significant impact of price transparency on traders' dynamic interactions based on 1-influential orders ($U(110) = 4271$, $z = -2.868$, $p < 0.01$). Table 5.7 further illustrates that the number of 1-influential orders per contract in an opaque market was doubled compared to a transparent market ($\text{Mean}_{\text{opaque}} = 4$, $\text{Mean}_{\text{tansparent}} = 2$).

A Mann-Whitney test based on the measures of 2-influential orders ($U(110) = 5669$, $z = -1.40$, $p > 0.16$), 3-infltuial orders ($U(110) = 6048$, $z = -0.18$, $p > 0.98$), and 2Out3-influetinal orders ($U(110) = 5756$, $z = -1.00$, $p > 0.31$), however, did not demonstrate the significant difference across the market with the two different price transparency conditions. According to Table 5.7, the average numbers of these influential orders per contract in both types of markets were almost zero. The possible reason is the limited number of buy and sell orders at the trader level. Table 5.5 shows that the average number of buy and sell orders per subject in a market was limited to approximately 15 and the number of subjects in a market did not exceeded 6. The limited numbers of subjects and buy and sell orders in the experimental prediction markets meant that they were unlikely to generate a high degree of influential orders. Thus, there was an insignificant difference between these measures across the two markets.

In line with the aforementioned results, we argue that when there are only a few actively participating traders in a prediction market, these traders update their opinions less frequently and the influence of one buy or sell order from a trader on a subsequent trader's trading decision is lower in a transparent market than in an opaque market. Accordingly, the following hypothesis (H_2) is supported.

H_2: When an internal prediction market has only a few actively participating traders, disclosure of price information leads to a decrease in traders' dynamic interactions.

Table 5.7 Summary Statistics for Traders' Dynamic Interactions at the Contract Level

Opaque market	*Transparent market*	*Number of 1-influential orders*	*Number of 2-influential orders*	*Number of 3-influential orders*	*Number of 2Out3-influential orders*
I	i	2 (1)	0 (0)	0 (0)	0 (0)
II	ii	5 (1)	0 (0)	0 (0)	0 (0)
III	iii	7 (6)	0 (1)	0 (0)	0 (1)
IV	iv	4 (0)	0 (0)	0 (0)	0 (0)
V	v	2 (3)	0 (0)	0 (0)	0 (0)
VI	vi	7 (1)	1 (0)	0 (0)	0 (0)
VII	vii	1 (0)	0 (0)	0 (0)	0 (0)
VIII	viii	2 (2)	0 (0)	0 (0)	0 (0)
IX	ix	2 (2)	0 (0)	0 (0)	0 (0)
X	x	7 (3)	0 (0)	0 (0)	1 (1)
XI	xi	0 (1)	0 (0)	0 (0)	0 (0)
XII	xii	3 (0)	0 (0)	0 (0)	0 (0)
XIII	xiii	10 (4)	1 (0)	0 (0)	1 (1)
XIV	xiv	1 (3)	0 (1)	0 (0)	0 (1)
XV	xv	3 (3)	0 (1)	0 (0)	0 (1)
XVI	xvi	1 (1)	0 (0)	0 (0)	0 (0)
XVII	xvii	4 (1)	1 (0)	0 (0)	1 (0)
XVIII	xviii	3 (4)	0 (0)	0 (0)	0 (0)
XIX	xix	9 (2)	0 (0)	0 (0)	0 (0)
XX	xx	5 (3)	0 (0)	0 (0)	0 (0)
XXI	xxi	5 (3)	0 (0)	0 (0)	0 (0)
XXII	xxii	4 (1)	0 (0)	0 (0)	0 (0)
Average		*4 (2)*	*0 (0)*	*0 (0)*	*0 (0)*

Note: Numbers in parentheses are from transparent markets.

5.5.4 Effects of Traders' Behavior on Market Information Aggregation Efficiency

We first calculated information aggregation efficiency, a percentage deviation of the transaction price from the equilibrium price in a prediction market. This percentage deviation measures to what extent the transaction price reflects the market consensus. Thus, it indicates how efficiently a market aggregates information from individual traders.

As discussed above, we considered two different contract prices, namely the last transaction price and the weighted average transaction price, to measure information aggregation efficiency. Table 5.8 exhibits the percentage deviation of each type of transaction price from the equilibrium price per market. A Wilcoxon test was performed on the 44 markets, including 22 opaque markets and 22 transparent markets. The result revealed that the choice of the contract prices did not differ significantly ($W(44) = 405$, $z = -0.59$, $p > 0.55$).

Table 5.8 Market Information Aggregation Efficiency

Opaque market	*Transparent market*	*Based on the last transaction price of a contract (%)*		*Based on the weighted average transaction price of a contract (%)*	
I	i	19.87	(2.11)	19.21	(2.80)
II	ii	10.56	(28.05)	11.25	(27.77)
III	Iii	6.27	(2.51)	5.11	(2.49)
IV	iv	7.70	(12.56)	8.20	(12.69)
V	v	1.56	(4.32)	1.04	(4.67)
VI	vi	7.33	(15.87)	7.01	(14.78)
VII	vii	8.54	(3.65)	9.19	(2.99)
VIII	viii	7.66	(19.36)	7.04	(18.28)
IX	ix	11.76	(4.80)	12.04	(4.81)
X	x	5.38	(9.89)	5.17	(9.55)
XI	xi	7.42	(9.00)	7.15	(7.86)
XII	xii	8.91	(12.85)	8.38	(14.87)
XIII	xiii	5.72	(4.15)	6.24	(4.15)
XIV	xiv	3.01	(5.34)	3.17	(7.72)
XV	xv	12.19	(8.46)	13.57	(15.48)
XVI	xvi	4.26	(3.98)	3.96	(4.19)
XVII	xvii	5.22	(6.02)	4.70	(5.46)
XVIII	xviii	7.01	(11.54)	7.31	(6.28)
XIX	xix	11.87	(7.99)	11.54	(8.39)
XX	xx	10.78	(4.18)	11.61	(4.94)
XXI	xxi	14.49	(5.33)	14.26	(4.10)
XXII	xxii	10.02	(11.82)	9.42	(7.23)
Average		*8.52*	*(8.81)*	*8.48*	*(8.70)*

Note: Numbers in parentheses are from transparent markets.

According to Table 5.8, market information aggregation efficiency based on the weighted average transaction price of a contract was slightly higher (opaque markets: $Mean_{last}$ = 8.52%, $Mean_{average}$ = 8.48%; transparent markets: $Mean_{last}$ = 8.81%, $Mean_{average}$ = 8.70%). Higher market information aggregation efficiency is desired in a prediction market. Therefore, we measure information aggregation efficiency based on weighted average transaction prices to validate the third and the fourth hypotheses.

We performed Spearman's tests to examine the effect of traders' participation activity and traders' dynamic interactions on market information aggregation efficiency. The results showed that traders' participation activity had a significant effect on market information aggregation efficiency, particularly, the number of shares in buy orders ($\varrho(44) = -0.46$, $p < 0.01$) and the number of shares in sell orders ($\varrho(44) = -0.41$, $p < 0.01$). The negative correlation implied that an increase in the number of shares in buy or sell orders lead to a decrease in the average percentage deviation of the transaction price from the dynamic equilibrium price of contracts in the market.

Although at the contract level, the results did not reveal a significant effect of number of transactions ($\varrho(44) = -0.13$, $p > 0.41$) and number of shares traded ($\varrho(44) = -0.18$, $p > 0.24$), overall, the aforementioned results manifested the positive effect of traders' participation activity on the reduction of market prediction error. Accordingly, the following hypothesis (H_3) is supported.

H_3: An increased level of traders' participation activity in a prediction market leads to higher information aggregation efficiency.

With regard to the traders' dynamic interactions, the contract-level results revealed that the effect of the number of 1-influential orders on market information aggregation efficiency was significant ($\varrho(44) = -0.39$, $p < 0.01$). The number of 2-influential ($\varrho(44) = -0.11$, $p > 0.49$) and 2Out3-influential orders ($\varrho(44) = -0.15$, $p > 0.33$), however, did not seem to be correlated with market predictive accuracy. The reason is due to the rare occurrence of these two indicators. In the 44 markets, both opaque and transparent, the occurrence of the 2-influential and 2Out3-influential orders was very limited (see Table 5.7) and there were zero 3-influential orders in the markets. This finding is in fact consistent with our previous case study, in which we concluded that one trader's influence on another based on the buy or sell orders concentrates on one degree influence.

Furthermore, at the trader level, the results showed that neither the number of Type I self-revisions ($\varrho(44) = -0.04$, $p > 0.79$) nor the number of Type II self-revisions ($\varrho(44) = -0.05$, $p > 0.75$) had a significant impact on information aggregation efficiency. Together with the analyses above, we argue that the number of self-revisions does not necessarily lead the transaction prices of contracts closer to the traders' agreed opinion, as a self-revision does not necessarily entail learning from other traders. However, the influential orders indeed reflect learning between traders in a market. Therefore, contract level indicators show the impact of dynamic interactions between traders on information aggregation efficiency.

The overall results discussed above manifested that traders' dynamic interactions significantly affects information aggregation efficiency. The negative correlation further illustrated that the enhanced interaction between traders reduces the deviation of transaction price from the dynamic equilibrium price of contracts in a market. Consequently, the following hypothesis (H_4) is supported.

H_4: An increase in traders' dynamic interactions in a prediction market leads to higher information aggregation efficiency.

5.5.5 Effects of Information Aggregation Efficiency on Market Predictive Accuracy

We first calculated the point prediction of each market and subsequently measured a market forecasting percentage error based on this market prediction and the corresponding actual result. The percentage error indicates the market predictive accuracy. The smaller this number, the greater the market predictive accuracy.

Similar to the measurement of information aggregation efficiency, we considered the last transaction price and the weighted average transaction price, to measure market predictive accuracy. Table 5.9 displays the prediction percentage error of each market based on these different prices. A Wilcoxon test was performed on the 44 markets. The result revealed that the choice of contract prices did not differ significantly ($W(44) = 301$, $z = -0.77$, $p > 0.43$).

This result is consistent with the findings of Plott and Chen (2002) drawn from their 16 internal prediction markets in HP. Another reason for this extreme similarity could be due to the short trading time of each market (10 minutes), which limited the number of transactions on each contract. Therefore, the weighted average transaction price and the last transaction price of a contract were quite close.

Table 5.9 further illustrates that the average market prediction calculated based on the weighted average transaction price of a contract was slightly more accurate (opaque markets: $Mean_{last} = 0.23\%$, $Mean_{average} = 0.22$; transparent markets: $Mean_{last} = 0.31\%$, $Mean_{average} = 0.30\%$). In turn, we adopted the market prediction percentage error based on weighted average transaction prices to validate our fifth hypothesis (H_5).

Table 5.9 Market Predictive Accuracy

Opaque market	*Transparent market*	*Based on the last transaction price of a contract (%)*		*Based on the weighted average transaction price of a contract (%)*	
I	i	0.48	(0.04)	0.48	(0.05)
II	ii	0.14	(0.76)	0.00	(0.45)
III	iii	0.53	(0.30)	0.55	(0.28)
IV	iv	0.08	(0.18)	0.08	(0.15)
V	v	0.73	(0.08)	0.72	(0.07)
VI	vi	0.13	(0.44)	0.12	(0.50)
VII	vii	0.13	(0.64)	0.12	(0.64)
VIII	viii	0.10	(0.39)	0.11	(0.23)
IX	ix	0.54	(0.10)	0.53	(0.12)
X	x	0.00	(0.50)	0.01	(0.51)
XI	xi	0.40	(0.05)	0.36	(0.06)
XII	xii	0.12	(0.05)	0.15	(0.05)
XIII	xiii	0.56	(0.23)	0.54	(0.19)
XIV	xiv	0.12	(0.44)	0.12	(0.53)
XV	xv	0.13	(0.03)	0.11	(0.01)
XVI	xvi	0.03	(0.41)	0.02	(0.40)
XVII	xvii	0.05	(0.06)	0.04	(0.08)
XVIII	xviii	0.52	(0.01)	0.60	(0.01)
XIX	xix	0.01	(0.39)	0.01	(0.53)
XX	xx	0.10	(0.99)	0.09	(0.93)
XXI	xxi	0.10	(0.08)	0.10	(0.25)
XXII	xxii	0.04	(0.61)	0.06	(0.60)
Average		*0.23*	*(0.31)*	*0.22*	*(0.30)*

Note: Numbers in parentheses are from transparent markets.

We performed a Spearman's test to examine the effect of information aggregation efficiency on market predictive accuracy. The results revealed that information aggregation efficiency is highly correlated with market predictive accuracy ($\varrho(44) = 0.47$, $p < 0.01$). The positive relationship further demonstrated that information aggregation efficiency had a positive effect on market predictive accuracy.

In this laboratory experiment, information certainty was high among participants. If all the participants bring information to the market and the market aggregates the participants' mean beliefs, the transaction prices of contracts should not deviate from the dynamic equilibrium prices of contracts. Moreover, with the higher certainty of the information, the transaction prices should reflect the actual results of the events to be predicted. Consequently, higher information aggregation efficiency leads to more accurate prediction. Accordingly, the following hypothesis (H_5) is supported:

H_5: Higher information aggregation efficiency of a prediction market leads to higher market predictive accuracy.

5.6 DISCUSSION

In the following sections, we further discuss the results of the laboratory experiments. Additional evidence drawn from the follow-up survey study is also incorporated.

The results showed that traders in opaque markets are more actively trading and learning than in transparent markets, particularly when the market was extremely thin. This finding can be explained from two major perspectives. First, this result is in line with the study of Flood et al. (1999). Flood et al. (1999) conducted an experiment to examine the effect of quote transparency, in which trade information was never revealed. Their study is similar to our experimental setting in which very limited trade information was presented to the subjects.

Their study revealed that when quote information is absent, traders must spend time searching for counterparties with whom to trade and traders show more aggressive pricing strategies. In our laboratory experiment, searching is indicated by a large number of buy and sell orders. Participants keep placing new buy and sell orders with different prices so as to find the possible matching orders for successful transactions. By contrast, the presence of quote information makes it easier for traders to trade with each other, and therefore, the trader's participation level is reduced. The same reason also explains why the opaque setting leads to higher self-revision behavior of participants in the laboratory experimental markets.

Searching entails the traders' learning based on other information sources, particularly, trade information in these markets. The results drawn from the questionnaire manifested that in an opaque market, the transaction prices of a contract were considered important to the participants. The following analyses support this finding and are based on the questionnaire that the subjects completed after each market.

As introduced in the research methods (see 5.3), after each market, subjects were required to fill in a questionnaire with regard to their use of different information sources. They were asked to give a score to each information source in a market. The scores indicated how important a specific information source was for the subjects to make their trading decisions. A Wilcoxon test was performed. The follow-up survey results revealed that the two different price information transparency conditions did not significantly affect subjects' perceived importance of various information sources for their trading decisions, except for the line chart ($W(96) = 586$, $z = -3.31$, $p < 0.01$) and the last transaction price ($W(96) = 780$, $z = -2.31$, $p < 0.05$) provided in the markets.

As Table 5.10 exhibits that in an opaque market, subjects considered the line chart ($Mean_{opaque} = 3.94$, $Mean_{transparent} = 3.57$) and the last transaction price ($Mean_{opaque} = 4.00$, $Mean_{transparent} = 3.63$) of contracts more important than in a transparent market. The line chart showed all the transaction prices of a contract during the entire trading time period and the last transaction price of a contract presented the most updated agreed opinion of that contract between different subjects in the market. Therefore, the aforementioned research finding implied that trade information becomes the most important information source for participants to extract other trader's opinions in opaque markets, when quote information is not available.

Table 5.10 Subjects' Perceived Importance of Different Information Sources

Information sources	*Transparent market*	*Opaque market*
Historical sales	2.79	3.12
Private information	4.25	4.17
Line chart of transaction prices	3.57	3.94
Last transaction price	3.63	4.00
Lowest sell/highest buy	4.30	--

It is noted that in transparent markets, the average score given to quote information exceeded even private information ($Mean_{quote} = 4.30$, $Mean_{private} = 4.25$). This highest score among all the information sources indicated that when quote information is available, participants in the market consider it most important in their trading decisions. The weight of trade information in their trading decisions reduces accordingly.

The second perspective to further explain the findings is based on the argument of Zhu (2002; 2004) and Granados et al. (2006). They argued that the effect of information transparency is not equivalent to all the participants in a market. The impact depends on the position of the participants. In other words, while some participants may benefit from the transparent market, others may not. For instance, buyers in general prefer a transparent market due to decreased search costs, increased possibility to discern products, and lower transaction price (Granados et al. 2006). Conversely, sellers, particularly, high-cost suppliers (Zhu 2002) or large market participants (Granados et al. 2006), often avoid trading in a transparent market, as it provides signals about their cost structure or their motivation to trade (Clemons and Weber 1990; Madhavan 2000).

In an internal prediction market, participants are the employees of the company. They are essentially all informed traders, as they have more or less inside information about the business practice being predicted. In turn, their buy or sell orders entail their private information. When the market is thin, which is often the situation of an internal prediction market, there is a very limited number of buy or sell orders. Thus, as soon as a participant places a buy or sell order, it will probably become quote information listed in the market. As a result, other participants can immediately learn and benefit from this information. Consequently, the participant who reveals this information loses the advantage of having private information. Therefore, when the market is considerably thin, an opaque setting in fact motivates traders to participate and learn more actively than a transparent condition.

Furthermore, this laboratory experiment study revealed the positive effect of traders' participation and dynamic learning in a prediction market on information aggregation efficiency and market predictive accuracy. The result is in accordance with the primary theories that information is aggregated through trader's trading activities (Plott 2000) and traders keep learning while trading (Gruca et al. 2005; Rhode and Strumpf 2004), and therefore, the market eventually reflects the sum of all available information about the future in the contract prices (Davis and Holt 1993; Fama 1965, 1970).

However, this finding is different from the findings of the empirical study conducted by Chen et al. (2010). They examined traders' participation activity and traders' dynamic interactions in prediction markets to evaluate early stage technologies. Their empirical field study did not reveal that an increase in traders' participation activity and dynamic interactions leads to an improvement in market performance. Our study, on the contrary, manifested that an increase in traders' participation level and in interactions leads to better market performance. Two possible reasons for those differences can be identified.

First, the measure of market performance is different between the two studies. In our laboratory experiments, we assessed prediction market performance based on absolute accuracy, against the actual outcome of the event being predicted. In their study, Chen et al. (2010) constructed internal prediction markets to predict the preference ranking of early stage technologies. This preference ranking corresponded to the evaluation of the technologies. The higher a technology was ranked, the greater its potential. The researchers assessed prediction market performance against the views of an expert panel. The closer the market prediction to the expert panel, the better the market had performed. This assessment of market performance in fact assumed that the expert panel generated a more accurate evaluation of early stage technologies than prediction markets. This assessment fulfilled the needs of the company in their study, which was seeking a more economic evaluation method to replace the costly expert panel. Nevertheless, in reality, it is unknown whether or not the aforementioned assumption holds.

The differences between the environments of the laboratory and field study are likely to be another reason. As discussed in Chapter 3, the differences between laboratory and field studies are noticeable. The study of Chen et al. (2010) was carried out in a real business environment, in which traders were employees and the environment could not be controlled by the researchers, while ours was conducted in a controlled laboratorial environment, in which subjects were university students. To further test the research model and understand information transparency on prediction markets, we will continue with the field experiments in the real business environment in the following chapter.

5.7 CONCLUSIONS

Advanced IT has enabled web-based prediction markets and the manipulation of information transparency in market design. However, little has been know about the effect of information transparency on prediction market performance. This chapter, therefore, aimed to investigate this research area. We particularly addressed two different conditions of price transparency, namely opaque and transparent, and focused on internal prediction markets where there are only a few actively participating traders. The objective of this chapter was to answer the following specific research questions:

RQ 2-1: *How does price information transparency in an internal prediction market with a limited number of actively trading traders influence the traders' behavior and further influence market information aggregation efficiency?*

RQ 2-2: *How does price information transparency in an internal prediction market with a limited number of actively trading traders influence the traders' behavior and further influence market predictive accuracy?*

The laboratory experiments showed that price transparency has an indirect effect on market performance through traders' behavior. In a thin prediction market, particularly in the context of an internal prediction market, the concealment of price information of buy and sell orders motivates traders to actively participate and learn compared to the revelation of the same information. Traders' active participation and interaction lead to a positive effect on market information aggregation efficiency and predictive accuracy.

The underlying reason is that the disclosure of a trader's buy or sell orders in fact exposes informed traders' private information and their improvement in estimation about the future event. When the number of traders is limited, these informed traders do not expect to obtain much from observing other's private information and updated estimation in the market. In turn, they are inclined to withhold their private information or their improved adjustment of their prediction based on learning. Consequently, price transparency in such a market is actually not desirable.

Moreover, in an opaque market, active participation and learning are necessary for traders to explore others' opinions about future events and make successful transactions. Accordingly, when the number of actively trading participants is very limited and all the traders are informed in a prediction market, price information, such as quotes, can be concealed for higher levels of trader participation and dynamic interactions, and eventually, higher information aggregation efficiency and more accurate market prediction, particularly when information about the future event in the market is highly certain.

This study makes an especially significant contribution to the research stream of information transparency. It extends current studies on information transparency from three different aspects. First, this study investigates the effect of information transparency on a new type of market. The existing literature and empirical studies on information transparency focus on B2B (Zhu 2002; 2004) and B2C (Granados et al. 2006; 2010) markets. Our research introduces the study of prediction markets. Second, our study follows the predecessor's call to examine the effect of different types of information in a market (Bloomfield and O'Hara 1999; Flood et al. 1999; Granados et al. 2008) by stressing quote price information. Third, we extend the generalizability of previous research on information transparency (Clemons and Weber 1990; Flood et al. 1999; Granados et al. 2006; 2010; Madhavan 2000; Zhu 2002; 2004) by comparing, linking and adding the research findings on the effect of price transparency on prediction market performance to this literature stream.

CHAPTER 6 INFORMATION TRANSPARENCY AND MARKET PERFORMANCE: A FIELD EXPERIMENT

6.1 INTRODUCTION

Current research focuses on numerous influential factors of prediction market performance, such as market size (Ho and Chen 2007; Ledyard 2006), market liquidity (Abramowicz 2006), composition of traders (Ledyard 2006; Surowiecki 2004), incentives (real money vs. play money) offered to traders (Luckner et al. 2008; Sauer 1998; Servan-Schreiber et al. 2004; Spann and Skiera 2003), and contract design (Ledyard 2006; Wolfers and Zitzewitz 2004). Information transparency, however, has seldom been taken into consideration. As discussed in Chapter 5, advanced IT has enabled the notable possibility of manipulating information access and revelation in a market, and therefore, the effect of information transparency on market performance is addressed in this dissertation.

This chapter focuses on a field study, which allows us to investigate price information transparency in an internal prediction market in a real business environment. As discussed in Chapter 3 (Research Methodology), the restricted control environment of laboratory experiments may conceal effects that can in fact appear in the real environment. Therefore, to further explore how price information transparency actually affects internal prediction market performance, we conducted field experiments. Similar to the laboratory experiments, this chapter aims to answer the second major research question of this dissertation:

$RQ_{main}2$: *How does information transparency in an internal prediction market influence market performance?*

Granados (2006) emphasized that IT not only increases potential for complete, accurate, real time and unbiased market information, but also gives the possibility to conceal or distort information. In turn, information can be strategically revealed, concealed, biased and distorted, depending on the goals or the positions of the participants in a market (Granados et al. 2010). Accordingly, information transparency may entail different levels. In other words, the type, amount and content of the information displayed in a market can vary. Therefore, we address different levels of price transparency in this field research.

The objective of this chapter is to examine the effect of different price transparency levels on information aggregation efficiency and predictive accuracy of internal prediction markets through traders' behavior. In turn, we construct the following two sub-research questions in this chapter.

RQ2-3: *How does a different level of price information transparency in an internal prediction market influence traders' behavior and further influence market information aggregation efficiency?*

RQ2-4: *How does a different level of price information transparency in an internal prediction market influence traders' behavior and further influence market predictive accuracy?*

This chapter extends our research to the effect of different price transparency levels on prediction market performance. The field experiments empirically test our hypotheses in a real business environment, enhancing the validity of our research findings. The results of this study show that the revelation of different traders' expectations rather than the highest or the lowest outstanding expectation on contracts leads traders to actively learn in an internal prediction market. However, in a fully transparent market, traders' learning activity level does not rise, but actually declines. The results of these field experiments further reveal that traders' learning in a prediction market leads to more efficient information aggregation. Information aggregation efficiency, as a market performance indicator, is especially useful when managers are interested in the consensus of their employees with regard to a future event. Last, although prediction markets in general have a robust forecasting ability, under highly uncertain circumstances market predictive accuracy is severely reduced.

Similar to the laboratory experiments, this field study makes several key contributions to extend current studies on information transparency and prediction market design (see Chapter 5). Particularly, the use of different information transparency levels in this research adds insights into the role of information transparency in the performance of internal prediction markets. Moreover, our development of the measurement of information aggregation efficiency not only fills a gap in the research on prediction markets but also gives the opportunity to assess market performance prior to the moment when the actual result is revealed. Given the fact that managers need and use prediction to manage the uncertain future, this measurement allows and enables them to use internal prediction markets in actual management. Last but not least, this field study demonstrates the importance of a company's commitment to the use of internal prediction markets to foster employees' active participation in the market.

The plan of the chapter is as follows. We first review the relevant theoretical foundation and construct the hypotheses accordingly. Thereafter, we present the overview of the subjects' participation in the experiments. Subsequently, we delineate the research design of the field experiments. Next, we discuss the measures adopted in this study. Afterwards, we present the research results based on the statistical analyses and validate the hypotheses. Additionally, we compare findings between this field study and the previous laboratory study. Finally, we conclude this study by answering the aforementioned research question.

6.2 THEORETICAL BACKGROUND

In this chapter, similar to Chapter 5, we study the overall conceptual model (see Figure 2-1). The difference focuses on the independent variable. In Chapter 5, we stressed the discussion of either transparent or opaque conditions. In this field study, we extend the conditions of information transparency to four different levels. In turn, we establish another two hypotheses, H_{1b} and H_{2b}, based on the relevant theories in this section.

6.2.1 Information Transparency Strategy and Traders' Participation Activity

Market transparency is affected by the underlying technological infrastructure of online and offline distribution channels (Cappiello et al. 2003; Sawhney 2001; Granados et al. 2008). Granados et al. (2008) asserted that the Internet is the major enabler of a structural increase in the levels of market transparency. In addition, market transparency also depends on the digital attributes of products (Granados et al. 2005; 2008). Essentially, the higher the digital attributes, the higher the potential for market transparency in the Internet channel. With regard to a contemporary prediction market, the trading mechanism is usually established based on Internet infrastructure, namely, an online prediction market. The products traded in an online prediction market, namely, the contracts, are fully digitized. Consequently, the potential for market transparency is high in an online prediction market based on Internet infrastructure.

To be specific, price information can be either disclosed or concealed and it can be disclosed more or less extensively. Therefore, traders may learn from information in the market that is more or less comprehensive or even complete. In turn, different levels of price transparency can be put forth in terms of the amount of price information displayed to the traders in a market.

Previous studies demonstrated that a market with the presence of quote information reveals information more rapidly and completely than a market without it (Bloomfield 1999; Madhavan 1995; Pagano and Röell 1996). Quote information is a type of pre-trade information which allows traders to infer other traders' expectations on contracts from their pricing behavior (Pagano and Röell 1996). As discussed above, traders in prediction markets do not collaborate but compete and are motivated to trade by different opinions (Surowiecki 2004). As a result, traders are likely to more actively participate in a market with quote information than without it, as long as the market is not confronted with an extremely limited number of traders.

However, when only the highest or the lowest outstanding quote information is displayed, traders can only observe the buying or selling price of a contract submitted by the most aggressive traders in the market. Informed traders benefit in this case, as they may earn more profit by trading with these aggressive traders (Madhavan 1995). Less informed traders, by contrast, benefit when more diverse quote information is displayed. In particular, there is always uncertainty about private information and the future. Thus, the increased amount of quote information helps traders extract more information from different traders to conceive their own expectations on the contracts. Consequently, when there are a number of traders in a prediction market, higher price transparency motivates traders to actively participate in the market.

Nonetheless, in the situation of full transparency, when all quote information is revealed in a prediction market, traders in general do not trade more actively. To be specific, a trader can easily identify if there is a matching buy or sell order in the market at the moment when he or she would like to trade. If there is no such matching order, he or she will simply wait instead of placing a desired order into the market. This is particularly true of informed traders. Informed traders are likely to conceal their private information in fully transparent markets, as everyone else will be able to observe and learn from their actions (Gruca et al. 2005; Rhode and Strumpf 2004). These traders benefit from profitable trading by possessing private information (Surowiecki 2004). In turn, the full transparency design is not likely to raise the participation activity level, and hence, the following hypothesis (H_{1b}) is constructed:

H_{1b}: In an internal prediction market, an increased disclosure of different traders' quote information leads to a higher level of traders' participation activity. However, the complete disclosure of traders' quote information does not further improve traders' participation activity.

6.2.2 Information Transparency Strategy and Traders' Dynamic Interactions

In Chapter 5, we delineated the function of quote information as a signal in a market from which traders can learn. Signals were named as they would carry information persistently from those with more to those with less information in a market (Spence 2002). In turn, traders expect to learn from other traders based on quote information in a prediction market. As a result, the disclosure of quote information gives the opportunity for traders to adjust their expectations on contracts iteratively.

Furthermore, the greater visibility of the individual orders can enhance the precision of traders' inferences about whether orders are driven by information or liquidity (Pagano and Röell 1996). Bloomfield and O'Hara (1999) also argued that when traders can discern the imbalances of buy or sell orders across the market, traders can learn any information from prices more quickly and therefore set their own prices more efficiently. These arguments suggest that traders' adjustment of expectations on contracts may increase and the influence of one trader on another may also be enhanced due to greater visibility of quote information.

Complete quote information, nonetheless, makes it more difficult for traders to discern information quality or the likelihood of potential outcomes. It also requires traders to spend more time analyzing information carried to the market. The explorative case study revealed that employees do not spend much time taking part in an internal prediction market in addition to their regular work. Traders are not likely to commit more time to analyzing quote information to adjust their expectation on a contract. Thus, traders' learning activity level is not likely to increase further.

Moreover, when all buy or sell orders are revealed in a market, the reaction of the traders will become similar to the situation in the previous laboratory experiments, when there are only a few traders in a market. Informed traders no longer actively update their opinion of future events, as other traders may learn from their improved estimation by observing the adjusted orders in the market. The resulting similar opinion between the traders prevents informed traders from making profitable trades. As individual adjustments become limited, the influence of one trader on another trader's learning becomes even more constrained. Consequently, the full transparency of price information hampers traders' interactions. Therefore, the following hypothesis (H_{2b}) is proposed:

H_{2b}: In an internal prediction market, an increased disclosure of different traders' quote information leads to an increase in traders' dynamic interactions. However, the complete disclosure of traders' quote information does not further enhance traders' dynamic interactions.

6.3 RESEARCH METHODS

We delineate the details of this field study in the following paragraphs, including the experiment design, the market mechanism design, the contracts in each market, the composition of the subjects, the incentive scheme and the experimental procedures.

6.3.1 Field Experimental Design

Similar to the laboratory experiments in Chapter 5, this field study focuses on quote information in prediction markets, as this pre-trade information is likely to influence traders' behavior. We identified four different levels of price information transparency in this study, including "opaque", "limited-transparent", "semi-transparent", and "full-transparent" (see Table 6.1).

In these field experiments, subjects were neither randomly assigned to one or more conditions nor required to take part in each of the conditions. Assignment to condition was by means of self-selection (Shadish et al. 2002). In other words, subjects were allowed to take part in any markets, as long as the markets were ongoing. This self-selection design is in line with traders' participation in real internal prediction markets, in which they take part based on personal willingness and interest.

Table 6.1 Operational Definitions of Price Transparency Levels

Transparency Levels	*Operational Definitions*
Opaque	Traders do not see any other trader's buy or sell orders, neither the price nor the number of shares
Limited-transparent	Traders see the highest outstanding buy order and the lowest outstanding sell order, including the price and the total number of shares
Semi-transparent	Traders see the highest three outstanding buy orders and the lowest three outstanding sell orders, including the price and the total number of shares. These buy and sell orders are presented to traders in a descending and an ascending order, respectively.
Full-transparent	Traders see all outstanding buy and sell orders, including the price and the total number of shares. These buy and sell orders are presented to traders in a descending and an ascending order, respectively.

There were four markets running in parallel every day. The names of the markets were vertically listed on the home page of the experiments. Subjects clicked the name of a market to enter that specific market. To avoid the situation that a subject did not participate in every market and always clicked the market listed in a particular position, we adopted a Latin square design (Field and Hole 2003) to order the experimental market sequences on the home page. Table 6.2 shows the markets and the corresponding transparency condition.

Table 6.2 Trading Day, Market and Price Transparency Level

Trading Day	*Markets*	*Price Transparency Level*
Day 1	I	Limited-transparent
	II	Semi-transparent
	III	Full-transparent
	IV	Opaque
Day 2	V	Full-transparent
	VI	Opaque
	VII	Limited-transparent
	VIII	Semi-transparent
Day 3	IX	Semi-transparent
	X	Full-transparent
	XI	Opaque
	XII	Limited-transparent

The field experiments were conducted in collaboration with Wasu TaoBao Co., Ltd (hereafter referred to as Wasu TaoBao). The company was founded by TaoBao and China Digital TV Media Group in 2010. The major business of Wasu TaoBao included two areas. One was iTV TaoBao, an online market on interactive TV with approximately 150,000 users. The other was www.taohua.com (hereafter referred to as taohua.com), an online B2B2C market specialized in digital products with approximately 370 million users. Taohua.com was the first as well as the largest online market of digital products in China. This online market focused on two product categories, including e-books and film and television. With more than 300 business providers, taohua.com had more than 30,000 different types of products and 10 million listed products. Based on taohua.com, Wasu Taobao aimed to promote a digital lifestyle in China with genuine, high quality and diversified products.

However, as the first online and newly established market of digital products, Wasu TaoBao has little information on customer behavior and sales of products on taohua.com. Furthermore, the market has been volatile and uncertain. The company, nevertheless, would like to predict some key performance indicators (KPIs) of taohua.com, based on their employees' knowledge and information. Therefore, Wasu TaoBao conducted the field experiments of internal prediction markets together with us, forecasting periodic KPIs of taohua.com.

6.3.2 Market Mechanism Design

A web-based continuous double auction mechanism was developed for the field experiments. The entire development of the market mechanism lasted for three months. The development included the user interface design, back-end programming, testing, modification and final implementation. Compared to the interfaces used in the previous case studies and the laboratory experiment, three major differences were introduced.

First, the language on the web-page was changed from English to Chinese, as the pilot studies (including six markets) with the English version revealed that the language barrier impeded the participation level of subjects.

Second, the display of outstanding orders in the semi-transparent and full-transparent conditions was modified. Instead of listing an order book on the left of the page, in the field experiment, the outstanding buy or sell orders were displayed in an overlay text when traders moved the mouse over the corresponding contract. This modification was carried out based on feedback from the subjects during the pilot studies. To illustrate this feature, we use full-transparent condition as an example (see Figure 6.2).

For instance, if the subject wanted to see the outstanding sell orders of contract "600-799", he or she could move the mouse to the corresponding "**所有**" (meaning: "All") in the column "**最低卖出竞价**" (meaning: "The Lowest Sell Order"). A blue window would appear, listing all outstanding sell orders of this contract in ascending order according to the selling price together with the number of shares in brackets.

Third, in contrast to the case studies and the laboratory experiments, where subjects were given a pre-set user account, subjects in this study were allowed to register a user account with his or her company email address and preferred password. The company email address allowed us to trace if any fraud or collaboration between the subjects existed. In addition, the subjects did not have to endeavor to remember the user name and password, which was an advantage as managing login details had seriously demotivated some participants in the pilot studies.

When a market started, every subject received an endowment, including 2,000 TaoBan and 20 shares per contract. TaoBan was the currency developed for the markets in this field study, implying Wasu TaoBao's company name and major business. Its abbreviation, TB, was stated on the web-based internal prediction markets (see Figure 6.2).

Figure 6.2 Screenshot of a Full-Transparent Field Experiment Market

6.3.3 Contract Design

The events being predicted and the contracts available were developed together with Wasu Taobao. We conducted 12 internal prediction markets inside the company to forecast its actual business KPIs in a certain month in 2011, such as the number of transactions or the number of page views of taohua.com. To avoid correlation between different markets, the 12 future events being predicted were mutually exclusive based on the managers' expertise in the business.

Every market had five contracts, representing five possible ranges of the outcome of a specific business KPI. Table 6.3 lists the contracts of each market. To clarify, to protect confidential information, we agreed to conceal the business KPIs predicted by the markets. Therefore, these markets are referred to as Market I to Market XII and the units of the contracts are concealed in the following discussions throughout the dissertation.

Due to high uncertainty about the business, the company was interested in an interval prediction rather than a point prediction, and in turn, the range of each interval was relatively larger. For example, in Market XI, the interval represented by one contract is from 5,000 to 9,999 In addition, not every contract had the same interval. For instance, in Market IV, the interval of contracts 1, 2 and 4 were 299; but the interval of contract 3 was 399 and the interval of contract 5 reached 1,700.

Table 6.3 Markets and Contracts in the Field Experiments

Markets	*Contract 1*	*Contract 2*	*Contract 3*	*Contract 4*	*Contract 5*
I	0-49	50-99	100-299	300-499	500-1,000
II	0-199	200-399	400-599	600-799	800-1,500
III	0-5	6-9	0-14	15-19	20-100
IV	0-299	300-599	600-999	1,000-1,299	1,300-3,000
V	40K-60K	61K-90K	91K-120K	121K-150K	151K-300K
VI	0-10K	11K-30K	31K-60K	61K-90K	91K-200K
VII	0.00-3.00%	3.00%-5.99%	6.00%-8.99%	9.00%-11.99%	12.00%-20.00%
VIII	¥0.00-¥1.99	¥2.00-¥4.99	¥5.00-¥7.99	¥8.00-¥10.99	¥11.00-¥20.00
IX	0-19	20-49	50-79	80-109	110-200
X	0-49	50-99	100-149	150-199	200-500
XI	¥0-¥4,999	¥5,000-¥9,999	¥10,000-¥14,999	¥15,000-¥19,999	¥20,000-¥50,000
XII	¥0-¥99	¥10-¥399	4¥00-¥699	¥700-¥999	¥1,000-¥2,000

6.3.4 Subjects

The field experiments were limited to employees of Wasu TaoBao. During our field experiments, the company had approximately 100 employees, including the executive team. We invited 30 employees to take part in the field experiments based on the discussion with the managers. This invitation list consisted of employees of all departments and the management team. Table 6.4 shows the departments and the corresponding number of invited employees. According to the General Manager, the composition of invited employees represented the actual distribution of employees in different departments.

Table 6.4 Composition of Invited Employees

Department / Team	*Number of Invited Employees*
Management	3
Product management	2
Product development	9
Business development	3
Operation	11
Marketing	1
HR	1
Total	*30*

6.3.5 Incentives

As Wasu TaoBao did not allow monetary incentives in these field experiments, small non-monetary incentives, such as a mug or T-shirt, were provided as a "prediction reward" and a "trading reward". The subject who owned most shares of the contract which represented the actual result in a market received the prediction reward. In each market, the subject who had the most TaoBan in his or her account at the end of a market received the trading reward. Similar to the laboratory experiments, the former reward was developed to motivate subjects to learn in the market and the latter was designed to motivate subjects to trade actively. Subjects were also informed that they would not be eligible for the market rewards if they did not place any buy or sell order in that market. Additionally, the reward winners were announced to the whole company as a "reputation reward".

6.3.6 Experimental Procedures

To kick off the internal prediction markets, a 30-minute plenary introduction was given to the invited subjects in Wasu Taobao's headquarter. During the introduction, the General Manager introduced the potential contribution of internal prediction markets to the company's decision-making processes and the experiment administrator demonstrated the operations of trading on the web-page. In the end, the subjects were allowed to register and play in four trial markets.

It should be clarified that the aforementioned four trial markets were not the same as the pilot study. We conducted the pilot study of six internal prediction markets with the participation of Wasu TaoBao's employees two months prior to the kick-off. The pilot study was carried out remotely, without the presence of the experiment administrator in the office of Wasu TaoBao. The pilot study provided us with feedback on the adjustment of the experimental design, such as the aforementioned mechanism design. The trial markets, however, aimed to familiarize employees with the operation of the web-based prediction market and help them understand their tasks as traders.

We conducted 12 markets (excluding the trial markets) on three consecutive days. Every day, four markets were listed and running in parallel during one specific hour. Each market corresponded with one transparency level. All registered subjects were allowed to participate in all markets. The allocation of one specific hour for prediction markets was designed based on the results drawn from the case studies. As employees were incline to focus on work during working hours and did not participate in the prediction markets after working hours, the General Manager of Wasu TaoBao decided to allocate one specific hour each day for the employees to participate in the internal prediction markets. Thus, the employees were more likely to actively participate in the markets.

During the one-hour trading time, the experiment administrator was also available onsite to answer questions or solve problems. Subjects could communicate with the administrator either by coming to the administrator's (temporary) office or via the company's internal instant message software, called Aliwangwang.

At the end of every trading day, a brief report regarding participation levels and trading activities, such as the highest and the lowest transaction prices of each contract, were sent to the subjects via email. According to the pilot studies, subjects were interested in the summarized information about a market. In turn, this feedback was considered helpful in motivating the subjects to participate in the next day's markets.

6.4 MEASURES

The measures in this field experiment involve four variables, i.e. trader's participation activity, trader's dynamic interactions, information aggregation efficiency, and market predictive accuracy. These measures are identical to the measures of the same variables in Chapter 4 and Chapter 5 (see 4.4 and 5.4 Measures).

To recap, the measure of traders' participation activity entails the contract level (i.e. number of transactions and number of shares traded) and the individual trader level (i.e. number of buy orders/sell orders and number of shares in buy orders/sell orders). Similarly, the measure of trader's dynamic interaction entails the contract level (i.e. 1-influential, 2-influential, 3-influential, and 2out3-influential orders) and the individual trader level (i.e. Type I and Type II self-revisions). With regard to information aggregation efficiency, we adopt the measurement we developed (see 5.4.1) based on the comparison between the transaction price and the dynamic equilibrium price of a contract. The measurement of market predictive accuracy followed absolute accuracy as developed by Plott and Chen (2002), which is assessed against the actual outcomes (see 5.4.2).

6.5 RESULTS

In this section, we discuss the results of the field experiments and validate the hypotheses based on these results. We first present the overview of the subjects' participation and the market prediction results in the experiments. Thereafter, we elaborate the results drawn from the field study according to the sequence of the hypotheses.

6.5.1 Overview of Subjects' Participation

41 subjects, namely, the employees of Wasu TaoBao, registered an account in these field experiments, and 17 of them were not from the invitation list. Having heard about the prediction markets, these employees proactively joined based on their own interests. This active, voluntary participation indicated the employees' interest in internal prediction markets.

Table 6.5 Overview of Market Design and Subjects' Participation

Markets	Price Transparency Level	Number of Active Traders
I	Limited-transparent	14
II	Semi-transparent	23
III	Full-transparent	15
IV	Opaque	12
V	Full-transparent	11
VI	Opaque	10
VII	Limited-transparent	8
VIII	Semi-transparent	7
IX	Semi-transparent	6
X	Full-transparent	8
XI	Opaque	8
XII	Limited-transparent	6
Average		*11*

Four employees participated in all 12 markets. The average number of active traders per market was 11. The highest number and the lowest number of active traders in a market were 23 and 6, respectively. Table 6.5 summarizes the design and the market size of each market.

On the last trading day, the number of traders declined due to a promotion activity on the taohua.com, which required most employees to follow that activity online. Therefore, the traders were distracted from the internal prediction markets on that day.

The 41 participating employees were drawn from all the departments in the company. Figure 6.3 shows the composition of the employees. The figure reveals that the largest proportion was from operational department, which also has the largest number of employees. Employees of this department may also have made up the largest proportion of traders because they possessed the most relevant information about the events the markets predicted.

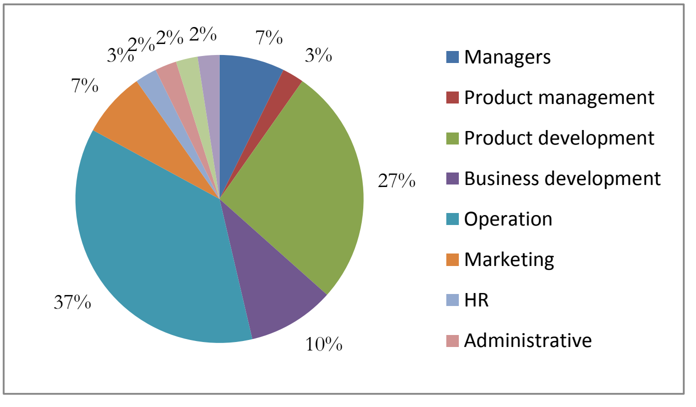

Figure 6.3 Compositions of Subjects

During the field experiments, two employees resigned. Their participation data in the markets before their designation remained valid in the following analyses. We also noticed that several subjects attempted to create double accounts. According to the market rules, every subject was allowed to create only one account based on his or her company email address. However, some non-company email address registrations were found in the administration system. This indicated that some subjects registered additional accounts. They probably intended to trade with unauthorized accounts so as to improve the performance of their genuine account and become the winner. Having detected the frauds, those unauthorized accounts were immediately disabled.

6.5.2 Effects of Information Transparency on Traders' Participation Activity

Similar to the analysis in the laboratory experiments, due to the different number of active traders in each market, we weighted the numerical values by the ratio of traders for the measurement at the contract level. Table 6.6 summarizes the statistics for the average trader's participation activity at the contract level under the four different price transparency conditions.

Table 6.6 Summary Statistics for Traders' Participation Activity at the Contract Level

Market	*Price transparency level*	*Weighted number of transactions*	*Weighted number of shares traded*
I	Limited-transparent	12	168
II	Semi-transparent	25	272
III	Full-transparent	15	169
IV	Opaque	11	136
V	Full-transparent	10	143
VI	Opaque	6	92
VII	Limited-transparent	18	299
VIII	Semi-transparent	14	192
IX	Semi-transparent	12	169
X	Full-transparent	14	215
XI	Opaque	10	173
XII	Limited-transparent	12	184
Average	*Opaque*	*9*	*134*
	Limited-transparent	*14*	*217*
	Semi-transparent	*17*	*211*
	Full-transparent	*13*	*176*

A Kruskal Wallis test did not revealed any significant difference between the number of transactions per contract in the markets with four different price transparencies ($x^2(3) = 5.6$, $p > 0.13$). According to Table 6.6, the largest difference in the number of transactions between different market transparency levels did not exceed eight ($Mean_{opaque} = 9$, $Mean_{limited} = 14$, $Mean_{semi} = 17$, and $Mean_{full} = 13$).

The number of shares traded per contract in the four types of markets did not differ either ($x^2(3) = 4.4$, $p > 0.22$). As Table 6.6 shows, the difference of the number of shares traded between different market transparency levels lay in the range between 6 and 83 ($Mean_{opaque} = 134$, $Mean_{limited} = 217$, $Mean_{semi} = 211$, and $Mean_{full} = 176$).

The insignificant difference between the four transparency levels was probably due to the relatively high traders' activity level. In the explorative case study described in Chapter 4, there were only 9 or 18 transactions per contract in a market during 12 trading days, compared to at least 9 transactions per contact in the internal prediction in this study. The relatively high level of traders' activity, hence, led to the similarly high number of transactions and number of shares traded.

Table 6.7 exhibits the statistics for the average trader's participation activity at the trader level in each market. Again, a Kruskal Wallis test was performed to further compare the corresponding measures across the 12 markets with different price transparency levels. The results showed that there was no significant effect of price transparency on trader's participation activity based on the measure of the number of buy orders ($x^2(3) = 4.7$, $p > 0.19$), number of shares in buy orders ($x^2(3) = 1.1$, $p > 0.78$), number of sell orders ($x^2(3) = 2.1$, $p > 0.54$), or number of shares in sell orders ($x^2(3) = 1.7$, $p > 0.63$).

Table 6.7 Summary Statistics for Traders' Participation Activity at the Trader Level

Market	*Price transparency level*	*Number of buy orders*	*Number of shares in buy orders*	*Number of sell orders*	*Number of shares in sell orders*
I	Limited-transparent	2	88	2	33
II	Semi-transparent	4	115	4	61
III	Full-transparent	3	113	2	41
IV	Opaque	3	115	2	34
V	Full-transparent	2	35	3	57
VI	Opaque	1	23	2	41
VII	Limited-transparent	2	66	4	64
VIII	Semi-transparent	1	22	2	31
IX	Semi-transparent	3	59	3	41
X	Full-transparent	2	60	2	33
XI	Opaque	3	68	3	61
XII	Limited-transparent	3	69	3	43
Average	*Opaque*	*2*	*69*	*2*	*45*
	Limited-transparent	*2*	*74*	*3*	*47*
	Semi-transparent	*3*	*65*	*3*	*44*
	Full-transparent	*2*	*69*	*2*	*44*

As Table 6.7 further illustrates, the average values of each measurement of different price transparency levels were in fact very close to each other. For instance, the average number of buy orders ($Mean_{opaque}$ = 2, $Mean_{limited}$ = 2, $Mean_{semi}$ = 3, and $Mean_{full}$ = 2) and sell orders ($Mean_{opaque}$ = 2, $Mean_{limited}$ = 3, $Mean_{semi}$ = 3, and $Mean_{full}$ = 2) in the four types of markets were almost the same. With regard to the number of shares in buy orders and the number of shares in sell orders, the largest difference did not exceed nine ($Mean_{opaque}$ = 69, $Mean_{limited}$ = 74, $Mean_{semi}$ = 65, and $Mean_{full}$ = 69) and three ($Mean_{opaque}$ = 45, $Mean_{limited}$ = 47, $Mean_{semi}$ = 44, and $Mean_{full}$ = 44), respectively.

This result was, again, related to the high activity level of traders. The number of active traders in these 12 markets (see Table 6.5) did not seem to be very large. However, within one hour and with four markets in parallel, the average number of buy or sell orders per trader reached two or three. This number exceeded the number of the same measure per trader per day in the explorative study.

According to the aforementioned results, it can be argued that the special trading time allocated to the employees motivated them to focus on participation in the internal prediction markets, ensuring the certain level of traders' participation activity, though the number of active traders was necessarily large.

In line with the aforementioned statistical analysis results, it can be argued that when there are a number of actively participating traders in an internal prediction market, their activity levels do not vary according to price transparency levels. In turn, the following hypothesis (H_{1b}) is not supported.

H_{1b}: In an internal prediction market, an increased disclosure of different traders' quote information leads to a higher level of traders' participation activity. However, the complete disclosure of traders' quote information does not further improve traders' participation activity.

6.5.3 Effects of Information Transparency on Traders' Dynamic Interactions

A Kruskal Wallis test was performed to examine traders' dynamic interactions. Analysis at the trader level revealed a significant effect of price transparency level on both Type I self-revisions ($\chi^2(3) = 14.7, p < 0.01$) and Type II self-revisions ($\chi^2(3) = 14.7, p < 0.01$).

A post-hoc test using Mann-Whitney tests with Bonferroni correction showed significant differences between opaque and semi-transparent markets (U(66) = 380, z = -2.21, $p < 0.05$), between limited-transparent and semi-transparent markets (U(64) = 292, z = -3.10, $p < 0.01$), and between semi-transparent and full-transparent markets (U(70) = 424, z = -2.36, $p < 0.05$).

These findings applied to both Type I and Type II self-revisions. In other words, the effects of different price transparency levels on traders' dynamic interactions at the trader level did not differ in terms of the type of self-revisions. When we compared the occurrence of these two types of self-revisions in each market, we noticed that the results were identical. This result implied that whenever a trader adjusted his or her expectation on a contract, the price difference between the previous and the updated order was at least 5% of the previous order.

Table 6.8 further illustrates that the average number of self-revisions per trader in semi-transparent markets was at least two times as many as in other markets ($Mean_{opaque} = 1$, $Mean_{limited} = 0$, $Mean_{semi} = 2$, and $Mean_{full} = 1$).

Table 6.8 Summary Statistics for Traders' Dynamic Interactions at the Trader Level

Market	*Price transparency level*	*Number of Type I self-revisions*	*Number of Type II self-revisions*
I	Limited-transparent	0	0
II	Semi-transparent	3	3
III	Full-transparent	1	1
IV	Opaque	1	1
V	Full-transparent	1	1
VI	Opaque	1	1
VII	Limited-transparent	1	1
VIII	Semi-transparent	1	1
IX	Semi-transparent	1	1
X	Full-transparent	1	11
XI	Opaque	2	2
XII	Limited-transparent	0	0
Average	*Opaque*	*1*	*1*
	Limited-transparent	*0*	*0*
	Semi-transparent	*2*	*2*
	Full-transparent	*1*	*1*

However, the occurrence of self-revisions did not differ between opaque and limited-transparent markets (U(58) = 383, z = -0.68, $p > 0.49$), opaque and full-transparent markets (U(64) = 499, z = -0.18, $p > 0.86$), and limited-transparent and full-transparent markets (U(62) = 414, z = -1.03, $p > 0.30$). As Table 6.8 demonstrates that the average number of self-revisions per trader in these markets lay between zero and one, the difference was in fact tiny. This indicated that traders adjusted their expectations on the contracts most frequently in semi-transparent markets.

At the contract level, the analyses addressed the weighted number of four different types of influential orders. According to the result of a Kruskal Wallis test, there was a significant effect of price transparency on traders' dynamic interactions based on the 1-influential orders ($x^2(3) = 25.9$, $p < 0.01$), the 2-influential orders ($x^2(3) = 18.5$, $p < 0.01$), and the 2out3-influential orders ($x^2(3) = 15.3$, $p < 0.01$).

A post-hoc test using Mann-Whitney tests with Bonferroni correction showed detailed results as follows. First, with regard to 1-influential orders, there was a significant difference between semi-transparent and the other markets (opaque: U(30) = 30, z = -3.77, $p < 0.01$; limited-transparent: U(30) = 37, z = -3.37, $p < 0.01$; and full-transparent: U(30) = 31, z = -3.78, $p < 0.01$). No significant difference was revealed between opaque and limited-transparent markets (U(30) = 98, z = -0.90, $p > 0.53$), between opaque and full-transparent markets (U(30) = 106, z = -0.52, $p > 0.80$), and between limited-transparent and full-transparent markets (U(30) = 92, z = -1.31, $p > 0.41$). In turn, the most 1-influential orders in semi-transparent markets; and the other three types markets did not differ.

Second, with regards to 2-influential orders, there was a significant difference between limited-transparent and semi-transparent markets (U(30) = 60, z = -2.96, $p < 0.05$) as well as between semi-transparent and full-transparent markets (U(30) = 60, z = -2.96, $p < 0.05$). No further significant difference was revealed between the other markets.

Third, no single 3-influential order occurred in all the markets (see Table 6.9). In turn, different price transparency levels in a market did not have any effect on this measurement.

Moreover, these follow-up analyses did not reveal any significant difference between all the markets in terms of 2Out3-influential orders. These insignificant differences were mainly due to the small number of this type of orders in all the markets (see Table 6.9).

The aforementioned results showed that the influence of one trader's order on another's in general occurred most frequently when the market was semi-transparent. Nevertheless, other markets did not differ significantly. The results drawn from the contract level and the trader level were convergent. Therefore, hypothesis (H_{2b}) is supported.

H_{2b}: In an internal prediction market, an increased disclosure of different traders' quote information leads to an increase in traders' dynamic interactions. However, the complete disclosure of traders' quote information does not further enhance traders' dynamic interactions.

Table 6.9 Summary Statistics for Traders' Participation Activity at the Contract Level

Market	*Price transparency level*	*Number of 1-influential orders*	*Number of 2-influential orders*	*Number of 3-influential orders*	*Number of 2Out3-influential orders*
I	Limited-transparent	0	0	0	0
II	Semi-transparent	3	1	0	1
III	Full-transparent	0	0	0	0
IV	Opaque	0	0	0	0
V	Full-transparent	0	0	0	0
VI	Opaque	0	0	0	0
VII	Limited-transparent	0	0	0	0
VIII	Semi-transparent	1	1	0	1
IX	Semi-transparent	1	0	0	0
X	Full-transparent	0	0	0	0
XI	Opaque	0	0	0	0
XII	Limited-transparent	0	0	0	0
Average	*Opaque*	*0*	*0*	*0*	*0*
	Limited-transparent	*0*	*0*	*0*	*0*
	Semi-transparent	*2*	*1*	*0*	*1*
	Full-transparent	*0*	*0*	*0*	*0*

To be specific, when there are a number of actively participating traders in an internal prediction market, showing different traders' quote information leads to a higher level of traders' interaction than showing no or the highest or lowest outstanding quote information. The complete disclosure of price information, as hypothesized, does not further enhance traders' interactions.

6.5.4 Effects of Traders' Participation Activity on Information Aggregation Efficiency

We first calculated information aggregation efficiency, a percentage deviation of the transaction price from the equilibrium price in a prediction market. This percentage deviation measures to what extent the transaction price reflects the market consensus. Thus, it indicates how efficiently a market aggregates the information from individual traders.

We considered the last transaction price and the weighted average transaction price of a contract to measure the information aggregation efficiency. Table 6.10 exhibits the percentage deviation of each type of transaction price from the equilibrium price per market. A Wilcoxon test was performed on the 12 markets: three opaque, three limited-transparent, three semi-transparent and three full-transparent. The result revealed that the choice between these two types of transaction prices did not yield significant difference of information aggregation efficiency ($W(12) = 24$, $z = -0.8$, $p > 0.42$).

Since the average value of the percentage deviation was slightly smaller based on the last transaction price, (opaque markets: $Mean_{last} = 40.75\%$, $Mean_{average} = 48.58\%$; limited-transparent markets: $Mean_{last} = 27.71\%$, $Mean_{average} = 48.58\%$; semi-transparent markets: $Mean_{last} = 22.91\%$, $Mean_{average} = 21.48\%$; and full-transparent markets: $Mean_{last} = 35.11\%$, $Mean_{average} = 35.20\%$), we adopted last transaction price in the following analyses.

To test the effect of traders' behavior on information aggregation efficiency, we examined the linear relationship based on Spearman's correlation coefficient. The results showed that traders' participation activity and dynamic interactions had a positive effect on information aggregation efficiency.

With regard to the traders' participation activity, contract level results revealed that the number of transactions had a significant correlation with information aggregation efficiency ($\varrho(12) = -0.81$, $p < 0.01$). The negative correlation indicated that a higher level of traders' participation activity leads to a smaller percentage deviation of the transaction price from the dynamic equilibrium price of a contract.

Nevertheless, the number of shares traded at the contract level ($\varrho(12) = -0.57$, $p > 0.54$) and the indicators at the trader level, including number of buy orders ($\varrho(12) = -0.23$, $p > 0.46$), number of shares in buy orders ($\varrho(12) = -0.20$, $p > 0.54$), number of sell orders ($\varrho(12) = 0.06$, $p > 0.85$), and number of shares in sell orders ($\varrho(12) = -0.32$, $p > 0.31$), did not show a significant correlation with information aggregation efficiency.

Table 6.10 Information Aggregation Efficiency Measurement per Market

Market	*Price transparency level*	*Based on the last transaction price of a contract (%)*	*Level of Information Aggregation Efficiency*	*Based on the weighted average transaction price of a contract (%)*	*Level of Information Aggregation Efficiency*
I	Limited-transparent	28.64	High	29.81	High
II	Semi-transparent	19.26	High	23.00	High
III	Full-transparent	21.03	High	52.76	Low
IV	Opaque	36.29	High	55.80	Low
V	Full-transparent	63.24	Low	33.10	High
VI	Opaque	42.37	Low	46.35	Low
VII	Limited-transparent	30.02	High	17.88	High
VIII	Semi-transparent	19.54	High	17.21	High
IX	Semi-transparent	23.93	High	24.23	High
X	Full-transparent	21.07	High	19.73	High
XI	Opaque	43.58	Low	43.58	Low
XII	Limited-transparent	24.46	High	45.10	Low
Average	*Opaque*	*40.75*	Low	*48.58*	Low
	Limited-transparent	*27.71*	High	*30.93*	High
	Semi-transparent	*22.91*	High	*21.48*	High
	Full-transparent	*35.11*	High	*35.20*	High

The aforementioned results implied that a trader's individual participation activity did not indicate the quality of the information carried by the traders. By contrast, the number of transactions at the contract level, representing the agreed opinion between traders, indicated the common recognition of the quality or certainty of the information carried into the market. Therefore, this indicator manifested the positive effect of traders' participation activity on the capture of market consensus in an internal prediction market. Accordingly, the following hypothesis (H_3) is supported.

H_3: An increased level of traders' participation activity in an internal prediction market leads to higher information aggregation efficiency.

6.5.5 Effects of Traders' Dynamic Interactions on Information Aggregation Efficiency

With regard to traders' dynamic interactions, all indicators at the contract level had a significant effect on information aggregation efficiency, including the number of 1-influential orders ($\varrho(12) = -0.66, p < 0.05$), the number of 2-influential orders ($\varrho(12) = -0.65, p < 0.05$), and the number of 2Out3-influential orders ($\varrho(12) = -0.65, p < 0.05$), except the number of 3-influential orders, as this degree of interactive influence did not occur among the traders.

At the trader level, the results did not reveal a significant effect of trader's self-revisions ($\varrho(12) = -0.83, p > 0.79$) on information aggregation efficiency (the number of Type I and Type II self-revisions were the same in all the markets, as previously discussed). This result implied that although traders updated their personal expectations on the contracts, this adjustment did not always influence another trader's adjustment. In turn, while different influential orders at the contract level had an impact on information aggregation efficiency, self-revisions at the trader level did not.

Overall, the aforementioned results demonstrated the positive effect of traders' dynamic interactions on the reflection of the traders' consensus in the transaction prices. Consequently, hypothesis (H_4) underneath is supported.

H_4: An increase in traders' dynamic interactions in an internal prediction market leads to higher information aggregation efficiency.

6.5.6 Effects of Information Aggregation Efficiency on Market Predictive Accuracy

We first calculated the point estimation based on the transaction prices of a market and identified the corresponding contract in each market. Table 6.11 exhibits the market prediction based on the last transaction price and the weighted average transaction price of contracts. The corresponding percentage error per contract compared to the actual result is also listed. However, it is important to note that these percentage errors are not equivalent to the actual results, though they are calculated based on the actual results using a master key to ensure confidentiality.

According to Table 6.11, it can been seen that the prediction based on the last transaction price and the weighted average transaction price of a contract was different in markets II, III, V, VII, and XI. As discussed before, the information aggregation efficiency based on the last transaction price in this field experiment was relatively higher than the one based on the weighted average transaction price. In line with our hypotheses (H_5) that higher information aggregation efficiency leads to more accurate market prediction, we reported the results based on the last transaction price to Wasu Taobao.

Table 6.11 Market Prediction

Market	Prediction based on the last transaction price of a contract		Prediction based on the weighted average transaction price of a contract	
	Predicted contract	*Percentage error (%)*	*Predicted contract*	*Percentage error (%)*
I	300-499	54.32	300-499	48.01
II	400-599	39.57	600-799	34.16
III	20-100*	55.32	15-19	59.57
IV	1,000-1,299	64.18	1,000-1,299	67.80
V	121K-150K	98.23	151K-300K*	98.09
VI	91K-200K*	64.95	91K-200K*	64.63
VII	6%-8.99%	44.94	9%-11.99%	41.88
VIII	¥8.00-¥10.99	40.27	¥8.00-¥10.99	41.60
IX	80-109*	69.48	80-109*	70.64
X	200-500	38.38	200-500	38.38
XI	¥20,000-¥50,000*	94.18	¥15,000-¥19,999	94.67
XII	¥700-¥999*	44.83	¥700-¥999*	46.14
Average	*Opaque*	*74.44*		*75.70*
	Limited-transparent	*48.03*		*62.04*
	Semi-transparent	*49.77*		*60.64*
	Full-transparent	*63.98*		*58.19*

To examine the effect of information aggregation efficiency on market predictive accuracy, we drew a scatter plot based on information aggregation efficiency and market predictive accuracy, and plotted a linear trend line. The trend lines drawn based on the last transaction price (see Figure 6.4a) and the weighted average price (see Figure 6.4b) of a contract showed that the prediction percentage error changes with the change in information aggregation efficiency in the same direction. This result indicated a positive correlation between information aggregation efficiency and market predictive accuracy, supporting H_5.

H_5: Higher information aggregation efficiency of a prediction market leads to higher market predictive accuracy.

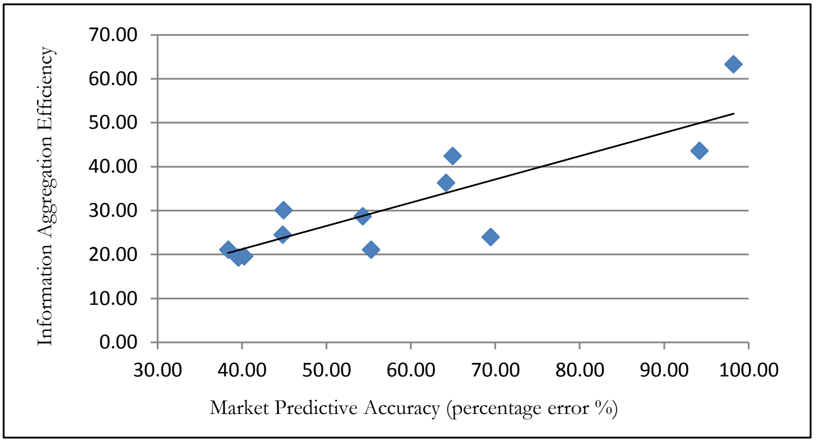

Figure 6.4a Market Performance based on the Last Transaction Price of a Contract

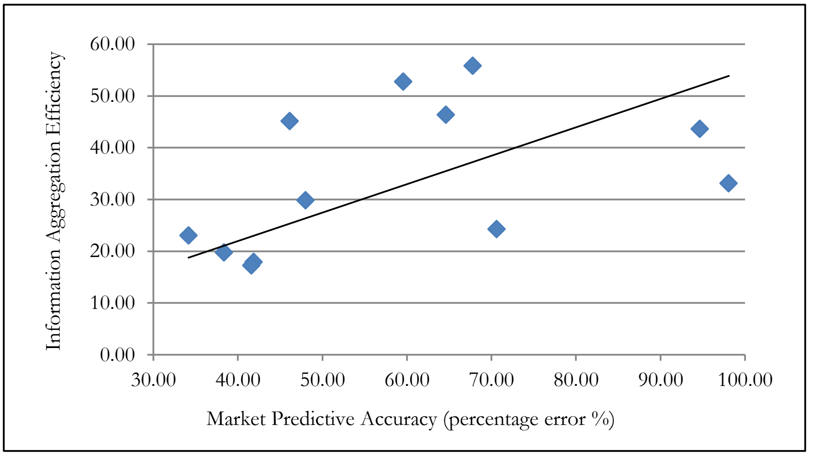

Figure 6.4b Market Performance based on the Weighted Average Transaction Price of a Contract

Later, when the actual result was available, if the predicted contract was the same as the actual one it was labeled with an asterisk "*" in the table above. As Table 6.11 illustrates, the prediction based on the last transaction price forecasted five markets accurately while the prediction based on the weighted average transaction price forecasted four markets accurately. This result further manifested that the prediction based on the last transaction priced was indeed more accurate than the one based on weighted average price.

6.6 DISCUSSION

In this section, we further discuss to the results drawn from the field experiments. We particularly focus on the influence of different price transparency levels on traders' behavior in an internal prediction market, explaining why the corresponding hypothesis (H_{1b}) is not supported. Moreover, we discuss market performance in terms of both information aggregation efficiency and market predictive accuracy.

6.6.1 Effect of Information Transparency on Traders' Behavior

The field experiments show that the transparency level of price information does not affect traders' participation level. This result is partially consistent with Bloomfield and O'Hara's (1999) research, which states that when trade information is disclosed, quote disclosure has little effect on market participation, as trade transparency provides information that cannot be obtained from quotes alone. However, considering the difference in experimental settings used in our study, our research findings are not fully explained by Bloomfield and O'Hara (1999). In their experimental setting, trade information was very much transparent, as an individual trader's trade information was available to other traders in a market. In our experimental setting, however, trade information was very limited, as only the last transaction price of each contract was presented, if any.

We argue that the most probable reason for traders' active participation is their interest in the internal prediction market, though the specific interests could range widely, such as the business practices being predicted, observing colleagues' opinions on the potential outcomes of the future event, and the fun of playing in the market. Evidence can be derived from prior studies on incentives. These studies suggested that a properly designed incentive scheme will motivate traders to trade and reveal information in prediction markets (Chen et al. 2009; 2010; Cowgill et al. 2008). It is implied that an incentive scheme is the fundamental factor that influences the employee's participation level in an internal prediction market.

Furthermore, the results of our empirical study show that the presence of the highest or the lowest quote information does not enhance the trader's learning activity compared to the absence of this information in an internal prediction market. A possible reason is that traders are very careful about signals in the market and quote information is in fact a signal in a market (Spence 1974; 1976). As information in a prediction market is asymmetric, traders are self-interested, and signals are an alterable observable attribute, some traders may place bids or asks which in fact deviate from their true expectations in order to affect other trader's estimations and to benefit from this behavior. Activities that are carried out to affect others are referred to as signaling and the individuals who act in this way are referred to as signalers (Spence 1974; 1976).

In practice, some traders may know that the signaler's information is not true, nevertheless, they would be glad to sell shares of the contract at the signaler's high price or to profitably buy shares of the contract at a low price from the signaler. However, in the real business environment, particularly in a new and dynamic business, employees in an internal prediction market hardly know whether information is true or not. As a result, to avoid being misled by a potential signaler, they may not adjust their expectations more frequently in a limited-transparent market than in an opaque market. The increased learning activity in a semi-transparent market in fact is the evidence. When more quote information of a contract is displayed in a prediction market, traders can better discern the quality of the information. Therefore, there is an increased level of trader's dynamic interactions in semi-transparent markets.

Furthermore, the complete quote information does not lead to an increased level of trader's dynamic interactions. In our empirical studies, the revelation of all quote information in a full-transparent market in fact reduced the dynamic interactions among traders compared to a semi-transparent market. This is probably because traders usually learn from more representative signals (Anderson and Holt 1997). In a semi-transparent market, we show the highest three outstanding buy orders and the lowest three outstanding sell orders. The price information of these outstanding bids or asks is the most representative signal, as it carries the most meaningful information.

Moreover, this finding can also be explained based on the phenomenon of information saturation in a market: beyond a certain point, more information does not improve market performance any further (Koppius 2002). Although we did not attempt to identify the point of information saturation in our study, if this point exists, providing information beyond that point, including the full disclosure of all the quote information, will not further improve the market performance through trader's behavior. Our result is in line with this argumentation.

6.6.2 Market Performance

We examine two aspects of market performance, namely information aggregation efficiency and predictive accuracy. This field study demonstrates an internal prediction market's robust ability to synthesize traders' agreed opinion. Even under dynamic and uncertain circumstances, a prediction market can reflect traders' mean belief into the transaction prices of contracts.

We further performed an ex-post analysis by dividing the information aggregation efficiency of the 12 markets into "low" and "high" categories. As the values of information aggregation efficiency essentially lay between 17 and 64, we classified the values between 17 and 40 as high efficiency and the values between 41 and 64 as low efficiency (see Table 6.10). Accordingly, based on the last transaction prices of contracts, nine markets were considered to have high information aggregation efficiency and two markets were considered to have low information aggregation efficiency. Based on the weighted average transaction prices of contracts, seven markets were considered to have high information aggregation efficiency and five markets were considered to have low information aggregation efficiency.

According to the analysis above, in our field research, approximately, 75% of the markets aggregated the information efficiently (see Table 6.10). This noticeable ability to capture traders' mean belief will allow practitioners to obtain employee's agreed opinions. Particularly, as a prediction markets' mechanism encourages the participants to reveal their true information (see 2.1.3.2), the use of prediction markets can help companies tackle the agency problem, specifically that the principal cannot verify that the agent has behaved appropriately (Eisenhardt 1989).

In terms of forecasting, the agency problem usually arises due to different goals or interests between the principal and the agent. For example, executives need true forecasts from employees; however, employees may reveal a lower forecast than they actually expect, hoping to receive possible additional rewards for performance that exceeded the estimate. Thus, the use of internal prediction markets can help executives to collect their employees' true forecast.

We noted a further interesting finding. We drew a line chart (see Figure 6.4) based on the average information aggregation efficiency in a market with a price transparency level in accordance with the data analyses shown in Table 6.10.

Although our study results did not reveal a direct effect of information transparency levels on information aggregation efficiency in a prediction market based on a Spearman's correlation coefficient test (Last transaction price: $\varrho(12) = -0.50$, $p > 0.10$; Weighted average transaction price: $\varrho(12) = -0.37$, $p > 0.24$), Figure 6.4 suggested a non-linear relationship between transparency level and information aggregation efficiency. In this specific field study with four different transparent settings, semi-transparent markets led to the most efficient information aggregation.

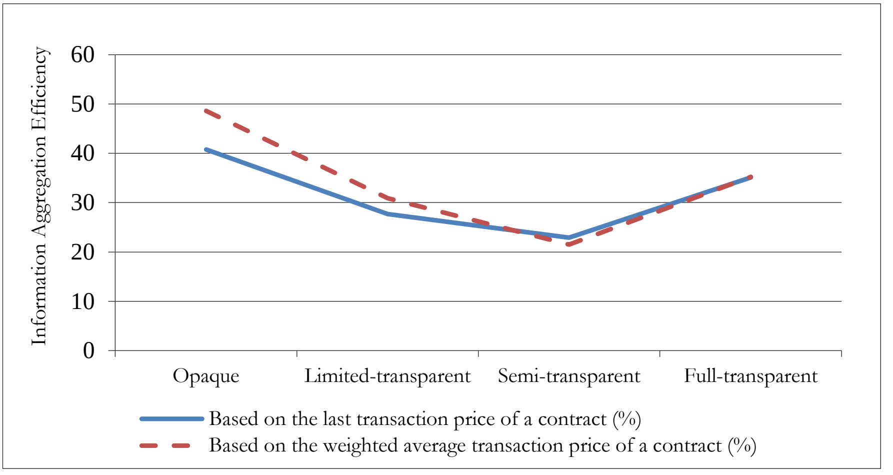

Figure 6.4 Information Transparency and Information Aggregation Efficiency

With regard to market predictive accuracy, our research manifested that internal prediction markets can make fairly accurate predictions, even under dynamic and highly uncertain circumstances. As discussed in the results, our field experimental environment was characterized by new business products within a complex industry and dynamic context. Under such highly uncertain conditions, 5 out of 12 markets, equivalent to 42%, predicted accurately; 6 out of 12 predictions were very close to the actual results, forecasting the contract adjacent to the accurate one. In turn, more than 90% of the markets in this field study made a satisfactory prediction. The well-known HP internal prediction markets predicted six out of eight accurately, equivalent to 75% (Plott and Chen 2002). However, their business environment was relatively more stable than Wasu Taobao. Therefore, compared to the 75% accuracy of HP, we argue that the 50% accuracy of the Wasu Taobao markets is significant.

The aforementioned argument is in light of Healy et al. (2010), who conducted laboratorial experiments to investigate prediction market performance under different levels of information complexity. They manipulated information complexity by altering the uncertainty of the events to be predicted. To be specific, in a relatively less complex environment, the markets only have one true-false event; in a relatively more complex environment, the market features three correlated events. Their empirical studies exemplified that the performance of prediction markets under higher information complexity, namely higher uncertainty, is less satisfactory than under lower information complexity. This difference is particularly evident when there are only a limited number of traders in a market.

Last but not least, it should be noted again that in this field study, because of the terms of our confidentiality agreement with Wasu Taobao, we did not receive the specific number of the actual result. Therefore, we were not able to calculate the percentage error as in Chapter 5. Under this constraint, it is in fact possible that some of the markets which predicted the adjacent contract to the actual one may have been very accurate, if the specific number of the actual result was very close to the predicted point estimation.

6.7 CONCLUSIONS

This research investigates the effect of information transparency on prediction market performance. We address different price transparency levels and internal prediction markets in a real business environment. The objective of this chapter is to answer the following two specific research questions: *How does a different level of price information transparency in an internal prediction market influence traders' behavior and further influence market information aggregation efficiency?* and *How does a different level of price information transparency in an internal prediction market influence traders' behavior and further influence market predictive accuracy?*

The findings of our empirical study reveal that price transparency affects market information aggregation efficiency through traders' dynamic interactions. Different transparency levels show non-linear effects on traders' dynamic interactions. When traders' buy or sell orders are disclosed in an internal prediction market, traders learn most actively: traders actively update their own expectations on the contracts; the influence of one trader's learning on another occurs most frequently; and the influence of one trader may sometimes extend to two different traders. However, the disclosure of all outstanding buy or sell orders does not further enhance traders' adaptive learning behavior.

Different price transparency levels, however, do not impact traders' participation level in an internal prediction market. This suggests that other design factors, such as incentives, should be considered to further motivate traders in internal prediction markets. For instance, Chen et al. (2010) demonstrated that traders can be motivated when their trading performance is associated with the endowment they receive.

Traders' participation and dynamic interactions positively affect the information aggregation efficiency of internal prediction markets. Higher participation and active learning behavior of traders leads to a close reflection of market consensus in the transaction prices of contracts. Moreover, when enough accurate information about the future exists in a market, the traders' consensus captured by the market indicates the actual outcome of the future event. In other words, a market with higher information aggregation efficiency is likely to predict accurately.

The different price transparency levels, however, do not necessarily have an effect on market predictive accuracy through traders' behavior or information aggregation efficiency when the environment is complex and uncertain. Even in dynamic environments, prediction markets have the ability to make accurate predictions.

This field study has two primary theoretical contributions. First, this research extends the literature on information transparency strategy by demonstrating how different information transparency levels influence market performance. Granados et al. (2005; 2008; 2010) contended that information transparency can be strategically designed in order to fulfill participants' goals or positions in a market, and eventually, lead to an improved market outcome. They argue that information transparency should be further studied as it contributes to market design. In this field experimental study, we designed four different transparency levels, representing four distinct uses of price information, including concealing the quote information, disclosing the most aggressive quote information, disclosing representative quote information from different traders, and disclosing complete quote information. The inclusion of these comprehensive information transparency levels encourages the research on information transparency to move from extreme cases to the exploration of optimization. Moreover, the focus on quote information particularly adds to the scant research on this type of information in information transparency and market design.

Second, our further development and implementation of the measurement of information aggregation efficiency especially contributes to the research stream of information aggregation in prediction markets (Bothos et al. 2012; Gruca et al. 2005; Plott 2000). We developed the measurement in accordance with the characteristics of prediction markets; aggregating the agreed opinion of traders in a market (Gjerstad 2004; Wolfers and Sitzewitz 2006a). Although our predecessors defined information aggregation efficiency, they did not develop the measurement accordingly. Instead, most of the researches measure the information aggregation efficiency of a prediction market against the actual result based on the assumption that there is enough accurate information in the market. However, in the increasingly dynamic business environment nowadays, this assumption does not always hold. Moreover, as illustrated in this field study, managers sometimes are more interested in the employees' opinion than in the accuracy of prediction. Therefore, our measurement, which measures to what extent the market aggregates the traders' mean belief, fills a gap in the research on the information aggregation efficiency of prediction markets.

CHAPTER 7 CONCLUSIONS

This dissertation focuses on contemporary web-based internal prediction markets and aims to improve market design from the perspective of information. It addresses two specific objectives. First, we aim to gain insights into traders' behavior in internal prediction markets. Second, our study investigates the effect of information transparency on prediction market performance. A better understanding of those factors will allow a prediction market to better serve managerial decision-making.

Our research entails two major research questions: (1) How do traders behave in an internal prediction market? and (2) How does information transparency in an internal prediction market influence market performance?

To answer those questions, we adopted a pluralist methodology, consisting of three empirical studies, including explorative case studies, laboratory experiments and field experiments. Table 7.1 summarizes the research design of each study, including the research focus, questions, method, unit of analysis and market design. The three studies adopted different research methods to supplement each other, and followed the use of sequential triangulation: the results drawn from each study were used to plan the method of the following study. This approach allowed us to conclude substantive and comprehensive overall findings.

The remainder of this chapter is structured as follows. First, we answer the research questions based on the main findings. Subsequently, we delineate the theoretical contributions of our study. Thereafter, we provide practitioners with managerial implications. Finally, we discuss the limitations of our research and suggestions for future research.

7.1 MAIN FINDINGS

We present the answers to the two major research questions of this dissertation in sequence in this section. We first elaborate traders' behavior in internal prediction markets. Thereafter, we delineate the indirect effect of information transparency in a prediction market on market performance.

Table 7.1 Overview of Research Methods and Designs

	Study 1: Explorative Case Studies	*Study 2: Laboratory Experiments*	*Study 3: Field Experiments*
Focus	Individual traders' behavior	Effects of price transparency on traders' individual behavior and market predictive accuracy	Effects of price transparency on traders' individual behavior and information aggregation efficiency
Major research questions	How do traders behave in an internal prediction market?	How does information transparency in an internal prediction market influence market performance?	How does information transparency in an internal prediction market influence market performance?
Research Method	Explorative case studies	Laboratory experiments	Field experiments
Unit of Analysis	Traders, contracts and markets	Traders, contracts and markets	Traders, contracts and markets
Prediction Events	Annual and periodic sales of a financial product in an international financial company	Annual sales of a product or service categories sold on www.taobao.com in 2008	Outcome of a Wasu TaoBao business sector in a certain month in 2011
Market Mechanism	Web-based continuous double auction; Dutch user interface	Web-based continuous double auction; English user interface	Web-based continuous double auction; Chinese user interface
Subjects	Regional sales managers of the international financial company's headquarter in the Netherlands	Students of Erasmus University	Employees of Wasu TaoBao
Incentives	Monetary	Monetary	Non-monetary
Reward bases	- Prediction result	- Attendance - Prediction result - Trading profit	- Prediction result - Trading profit

7.1.1 Traders' Behavior

Traders' behavior in this research focuses on two major aspects, participation and dynamic interactions. In general, traders do not actively participate in an internal prediction market. First, a small number of employees participate in a market. A company may invite a large number of employees to take part, however, only a few employees become actively participating traders, who frequently trade in the market during the entire trading time period. Second, employees spend very limited time trading in a market. Even those actively participating traders do not trade every day or trade on all contracts.

The low participation of employees in internal prediction markets has two main causes. First, most employees are motivated to trade based on their curiosity about prediction markets (Borison and Hamm 2009); this curiosity can quickly drop as traders' interest in the market changes or declines (Dye 2008). Particularly, after they gain experience in one market, they are no longer interested in the following markets. Second, employees' trading time is constrained, as they must fulfill their work duties during working hours. Hanson (2006) argued that participation in an internal prediction market requires that employees allocate time and effort from their regular work. The time and effort constraints, in fact, imply that employees regard participation as a part of their job. Employees do not consider participation to be the priority during the workday, nor do they trade after hours. This is the underlying reason why the entertainment value (Wolfers and Zitzewitz 2004), which drives traders to actively participate in public prediction markets, does not work in internal prediction markets.

Dynamic interactions between traders indicate the learning of traders in a market. First, employees in an internal prediction market keep learning and incorporate new information into their trading activities (Bondarenko and Bossaerts 2000; Gruca e al. 2005; Rhode and Strumpf 2004). They do not trade actively, but they update their opinions whenever they trade. The empirical study reveals that more than half of the buy or sell orders entail an update of traders' opinions; the difference of prices between the previous order and the following order is always at least 5%, considered to be statistically significant. Additionally, employees learn from different information sources, particularly newly acquired private information.

Second, one trader's order has an impact on another trader's order, leading to an identical change of a different trader's opinion. However, this impact is limited to two consecutive orders. One trader's order rarely influences more than two subsequent orders from different traders, as employees rely on private information most when they make trading decisions.

Moreover, an unusual price of an order is likely to lead to an information cascade in an internal prediction market, as employees believe that another trader has special private information about the future event. In turn, they quickly respond to this signal (Bondarenko and Bossaerts 2000; Gruca et al. 2005; Rhode and Strumpf 2004) and follow the same direction of change. "Marginal traders" are able to discern the quality of the signal (Forsythe et al. 1992; Oliven and Rietz 2004). If the information carried by the signal is not accurate, marginal traders can correct the market. However, market correction requires time.

7.1.2 The Effect of Information Transparency on Market Performance

Information transparency affects market performance indirectly via traders' behavior. The effect of the level of information transparency on traders' behavior is also moderated by market size. To be specific, when a market has only a few actively participating traders, the concealment of price information of buy and sell orders leads to a higher level of traders' activity and interactions than the disclosure of the information. Two primary reasons are identified. First, when price information is concealed, traders must spend time searching for counterparties with whom to trade, and therefore, they follow a more aggressive pricing strategy (Madhavan 1995), placing a large number of buy and sell orders and changing the order price every time.

Second, employees in an internal prediction market have certain relevant information about the future event, though the information they have differs. In turn, their individual order prices entail their private information. When the market discloses the price information and the market is thin, as soon as an informed trader places a buy or sell order, he or she reveals his or her private information to others. As a result, while other employees immediately learn and benefit from this private information, the informed trader loses the advantage of having private information (Surowiecki 2004). Therefore, when a market is quite thin, concealment rather than disclosure of price information motivates employees to participate and learn in the market.

When a market has relatively more actively participating traders, different price transparency levels have a non-linear effect on traders' learning activities. The disclosure of different traders' price information leads to an increase in traders updating their opinions and the influence of one trader's learning on another. The variety of price information allows employees to infer others' expectations on the contracts (Pagano and Röell 1996), provides them with more comprehensive information (Granados et al. 2010), and enables them to discern accurate information (Kahn et al. 2002) and learn in the market. Complete price information, however, does not further enhance the dynamic interactions between traders due to the phenomenon of information saturation in a market (Koppius 2002). Nevertheless, price transparency does not affect traders' participation level in such a market.

Furthermore, traders' participation and dynamic interaction have a positive effect on the information aggregation efficiency of a prediction market. In other words, increases in traders' participation and learning activities enhance the ability of the market to reveal traders' mean belief. Higher information aggregation efficiency indicates more accurate market prediction. However, a higher level of traders' participation and enhanced traders' dynamic interactions do not necessarily lead to more accurate market forecasts, as the information in the market is not always highly certain (Sunstein 2006a).

The aforementioned research findings are summarized by the following revised research model (Figure 7.1) and the corresponding hypotheses:

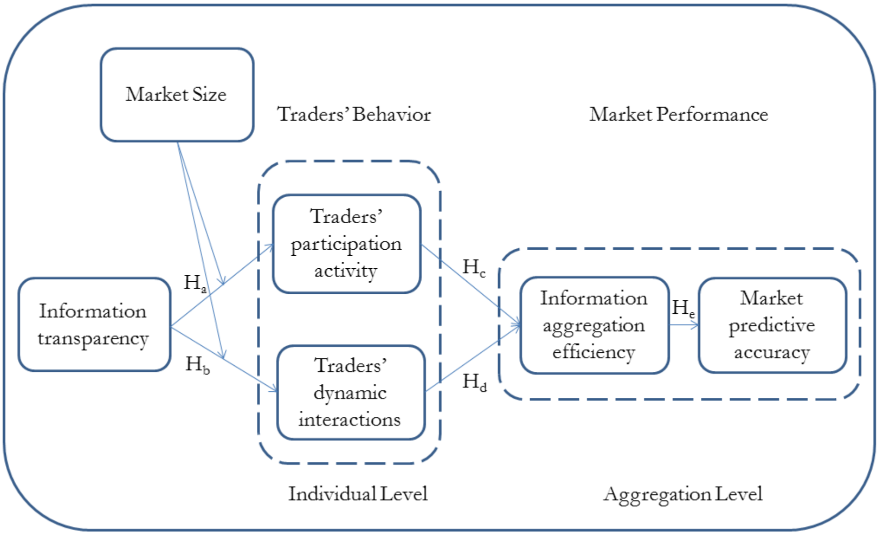

Figure 7.1 Revised Research Model

H_a: In a thin internal prediction market, concealment of quote information leads to higher traders' participation activity; in a thick internal prediction market, the transparency level of quote information does not have an effect on traders' participation activity.

H_b: In a thin internal prediction market, concealment of price information leads to a greater prevalence of traders' dynamic interactions; in a thick internal prediction market, greater disclosure of different traders' quote information leads to a greater prevalence of traders' dynamic interactions than either concealment or full disclosure of traders' quote information.

H_c: An increased level of traders' participation activity in a prediction market leads to higher information aggregation efficiency.

H_d: An increase in traders' dynamic interactions in a prediction market leads to higher information aggregation efficiency.

H_e: Higher information aggregation efficiency of an internal prediction market leads to more accurate prediction market forecasts.

7.2 THEORETICAL CONTRIBUTIONS

This dissertation contributes to the literature on information transparency and prediction markets. With regard to information transparency, first, we theoretically develop and empirically test the impacts of information transparency in the context of prediction markets. This extends previous studies on information transparency that focused on B2B (Zhu 2004) or B2C markets (Granados et al. 2010). Prediction markets represent a different type of market, namely a double auction. Particularly considering the similarity between prediction markets and financial markets (Hanson 2006), the information transparency results of this study are likely to hold for financial markets.

Second, this dissertation contributes to the research stream of transparency strategy. Following the seven key components of transparency strategy identified by Granados et al. (2010), our study particularly focuses on information elements and potential actions (see 2.2.3). To be specific, we investigate the effect of price information transparency on traders' behavior and prediction market performance.

Within the scope of price transparency, this dissertation extends the current literature on the effect of different types of price transparency on markets. Price information falls into several categories, such as quote, trade, and order flow. Different price information components have different effects on a market, and even the same type of price information may have different impacts on different types of markets (Bloomfield and O'Hara 1999). By investigating quote information and its transparency effect in prediction markets, this research has further explored price transparency in designing new market types.

With regard to the literature on prediction markets, first, this research adds to theory development in prediction markets. Prior research primarily focused on the effects of incentives (such as Bondarenko and Bossaerts 2000; Gruca et al. 2005; Malone 2004b; Rhode and Strumpf 2004), market size (such as Berg et al. 2008; Tetlock 2007) and contract design (such as Wolfers and Zitzewitz 2004; 2006b) on prediction market forecasting accuracy. This dissertation addresses prediction markets from the perspective of information transparency. Advanced information technologies have driven the adoption of web-based prediction markets. This research further shows how information technologies can affect the performance of web-based prediction markets. In turn, this dissertation fills the research gap on contemporary web-based prediction markets and links the discipline of IS to the study of prediction markets.

Moreover, this research distinguishes information aggregation efficiency and market performance for the analysis of aggregation. Existing research on prediction markets mostly focused on market efficiency and measured this variable by assessing the market's forecasting accuracy (such as Gruca et al. 2005; Plott 2000). This measurement is based on the principle that if a market aggregates information efficiently, all the relevant information will be reflected in the price of contracts, and therefore, the market prediction ought to be accurate. Nevertheless, it neglects the truth that, in reality, no one has accurate information about the future. Moreover, a market successfully aggregates information, even information that does not necessarily lead to an accurate prediction. The reverse is also true: an inaccurate market forecast does not definitely indicate inefficient information aggregation.

Subsequently, we propose a measurement of information aggregation efficiency. This not only enables the assessment of information aggregation in a prediction market but also fulfills the increased need of companies to use prediction markets to collect employees' agreed opinion rather than to forecast specific outcomes. Additionally, our study on the relationship between information aggregation efficiency and market predictive accuracy further contributes to the research stream of prediction markets by theoretically developing and testing the relationship between these two variables.

Furthermore, this research incorporates traders' individual activities to explain the effect of information transparency on market performance. Specifically, this research investigates how price transparency influences traders at the individual level and the results at the aggregate level of prediction markets. We take two different individual activities into consideration that are likely to affect the aggregation level, namely traders' participation level and traders' dynamic learning behavior. Indeed, Bapna et al. (2004) contented that understanding individuals' activities is crucial to enhance the design of online markets. Our study on individual traders' activities, in turn, contributes to the design of web-based prediction markets.

Finally, this dissertation adds to the research on new applications of prediction markets inside a company, which are referred to as internal prediction markets (Hahn and Tetlock 2006; Wolfers and Zitzewitz 2004). Although the literature contains references to numerous companies, such as Dentsu (Pethokoukis 2004), Eli Lilly (Hahn and Tetlock 2006; Pethokoukis 2004), Intel Corporation (Malone 2004), Microsoft (Hahn and Tetlock 2006), and Siemens (Ortner 1998), that are actively employing prediction markets in their businesses, little scientific research has been done on the implementation and performance of these internal markets. The current research on internal prediction markets is limited to HP (Plott and Chen 2002) and Google (Cowgill et al. 2008). The lack of empirical research on internal prediction markets may impede the adoption and contribution of prediction markets in the real business world. Therefore, this dissertation extends the literature on internal prediction markets and encourages its practice in business.

In addition to literature, this dissertation also contributes to research methodology by using multiple research methods. Multi-method research is desired but not common in IS. Mingers (2001) showed that only a tiny proportion of IS empirical research adopted multiple methods; two-thirds of these research combinations involved similar approaches, such as surveys, interviews, and/or case studies. He contended that these types of research combinations are not equivalent to the desired pluralist methodology of a wide diversity of different approaches. It is in fact just a narrow spectrum centered around traditional approaches with very few cross-paradigm linkages. This dissertation adopts various different research methods, including case studies, laboratory and field experiments, and surveys. Therefore, this dissertation adds to IS research with a pluralist methodology and demonstrates the feasibility of multi-method research in IS.

7.3 MANAGERIAL IMPLICATIONS

In addition to the theoretical contributions, the contributions to practitioners are of paramount importance to our research. In this section, we discuss the managerial implications of our study.

7.3.1 Use of Internal Prediction Markets

Prediction markets are generally considered as a forecasting tool, and therefore, their forecasting accuracy is always assessed. Similar to previous research, our research, particularly the case studies and field experiments, show again that internal prediction markets are able to forecast an accurate outcome of future events. Moreover, the one-hour ad-hoc play time adopted by Wasu Taobao demonstrates that an internal prediction market has the possibility to forecast within very limited market duration.

Besides forecasting, prediction markets are used for many other management purposes, such as idea selection and information aggregation (Chen and Plott 2002; Chen et al. 2009; Chen et al. 2010; Hanson 1992; Hanson 1995; Ottaviani 2009; Passmore et al. 2005; Spears et al. 2009). In the case of Wasu Taobao, its managers aimed to learn employees' agreed opinions on sales. The corresponding field experiment illustrates the application of internal prediction markets as an information aggregation mechanism. Particularly, with the proposed measurement of information aggregation efficiency in this dissertation, managers are able to evaluate to what extent the market outcome reflects the agreed opinions of employees. This may also become an indicator for managers to decide whether or not the market forecast should be adopted.

Furthermore, the current empirical studies on internal prediction markets are limited to the western business context. It is yet unclear if any difference, such as culture, between the West and the East, may influence the feasibility of using prediction markets inside Eastern companies. Wasu Taobao's internal prediction markets, conducted in a new, dynamic and highly uncertain business environment, not only demonstrate the considerable potential for prediction markets in managerial decision-making but also manifest the feasibility of connectivity and collaboration between the East and the West through efficient IS.

Finally, according to the follow-up study of our case study, employees bring updated private information into a market by incorporating this information into their trading decisions. This behavior not only positively affects market performance but also meets managers' expectations, as they use prediction markets to aggregate updated inside information from the front line.

7.3.2 Conduct of Internal Prediction Markets

Given the opportunity to design, establish and operate numerous internal prediction markets during the research, we have gained insights into conducting an internal prediction market. These insights inductively yield guidance for practitioners to build up a prediction market in their own companies. We identify four major phases of conducting an internal prediction market: design, development, implementation and evaluation (see Figure 7.2a).

In the first phase of design, all the necessary elements of an internal prediction market, such as contracts, traders, incentives, market duration and information presentation, should be considered and determined. For instance, with regard to traders, the practitioner should consider access to the market, whether employees will be allowed to self-select to be a trader or if participation will be by invitation only. In the latter case, the practitioner must determine the number of invited employees. The proportion of very active traders is commonly low. In our empirical studies, the rate was approximately 12%. Therefore, the company may invite a relatively larger group of employees in order to ensure a sufficient group of active traders in the market. Moreover, the department affiliation of the invited employees ought to be carefully considered. Information brought by the employees from different departments may vary. The relevance and diversity of information about a future event are crucial to market performance. Consequently, when practitioners design an internal prediction market, they must take factors into consideration that influence market performance.

In the second phase of development, the applicable support infrastructure must be developed, including the web-based trading interface, the associated database, user account management and technologies and methods of communicating with traders. System or software testing and the pilot study are crucial, as technical problems may demotivate employees to participate. Traders' inactivity, in turn, hampers information aggregation and eventually market performance. In addition, due to competition and self-interest, there could be fraud or manipulation performed by some traders in an internal prediction market. For example, in our field experiments, we found that a single employee had double registered with two different email addresses. We successfully detected this behavior as we required each employee to register with his or her own company email address, which is unique to each employee. Once a non-company email address was found in the system, we could immediately eliminate that account. It is hard to prevent certain frauds, and overly restrictive game rules may reduce traders' activities. However, companies must develop certain methods to detect fraud and measures to correct manipulations.

In the following phase of implementation, an internal prediction market is launched. Before the kick-off of the prediction market, an introduction and a trial play for traders are recommended. As not every trader has knowledge or experience about trading in a prediction market, the trial play with assistance can help them learn quickly. Furthermore, a debriefing of market performance and an announcement of the winning traders is strongly recommended. The "game" results usually motivate traders to continue playing in subsequent prediction markets. According to our field experiments, we observed that traders were eager to know the winning results. This is probably due to the competition institution of the market. Winners showed pride and excitement after debriefing and became stable active traders. Additionally, debriefing can be companywide, even if only a few employees participated in a market. This companywide debriefing may remind or inspire some employees to become new traders. We considered this an important reason why many uninvited employees later actively registered and joined the internal prediction markets of Wasu Taobao.

The last phase of evaluation is particularly important if a company would like to adopt internal prediction markets as its long-term decision-making tool, as the evaluation can help the company continuously improve the operation of internal prediction markets and eventually better serve the company's management. This evaluation should not only concentrate on market performance, such as forecasting accuracy, but also traders' feedback. The company may carry out an online survey to understand the difficulty of implementation and develop the solution accordingly. For example, in our case study, a follow-up online questionnaire study among the traders revealed that constrained time was the major reason for employees not taking part in the internal prediction markets actively or even at all. In the trial field experiment of Wasu Taobao, the same issue was revealed. Accordingly, in the following experimental internal prediction markets, Wasu Taobao proposed one-hour ad-hoc play time of prediction markets every day. Given this top-down encouragement, the participation and the trading activities of employees were remarkably increased.

Last but not least, it should be noted that for a single internal prediction market, the four phases occur chronologically. However, for a company running prediction markets in the long run, these phases in fact form a cycle (see Figure 7.2b). The previous market experience is always the foundation for improving the following ones.

7.4 LIMITATIONS

In this dissertation, we investigate traders' learning behavior in accordance with their trading activities in a market. There in fact can be another supplementary measurement by comparing a trader's individual estimation of a future event before and after a prediction market. This comparison can indicate whether traders learn in a market. In the case study, we could not observe traders' initial personal estimation of sales in advance of the prediction markets. We attempted to make up this limitation in our later field experiment. We asked invited employees to fill in their personal predictions of the future events via an online questionnaire. Unfortunately, few employees provided their individual predictions. Consequently, we again could not execute this measurement of traders' learning.

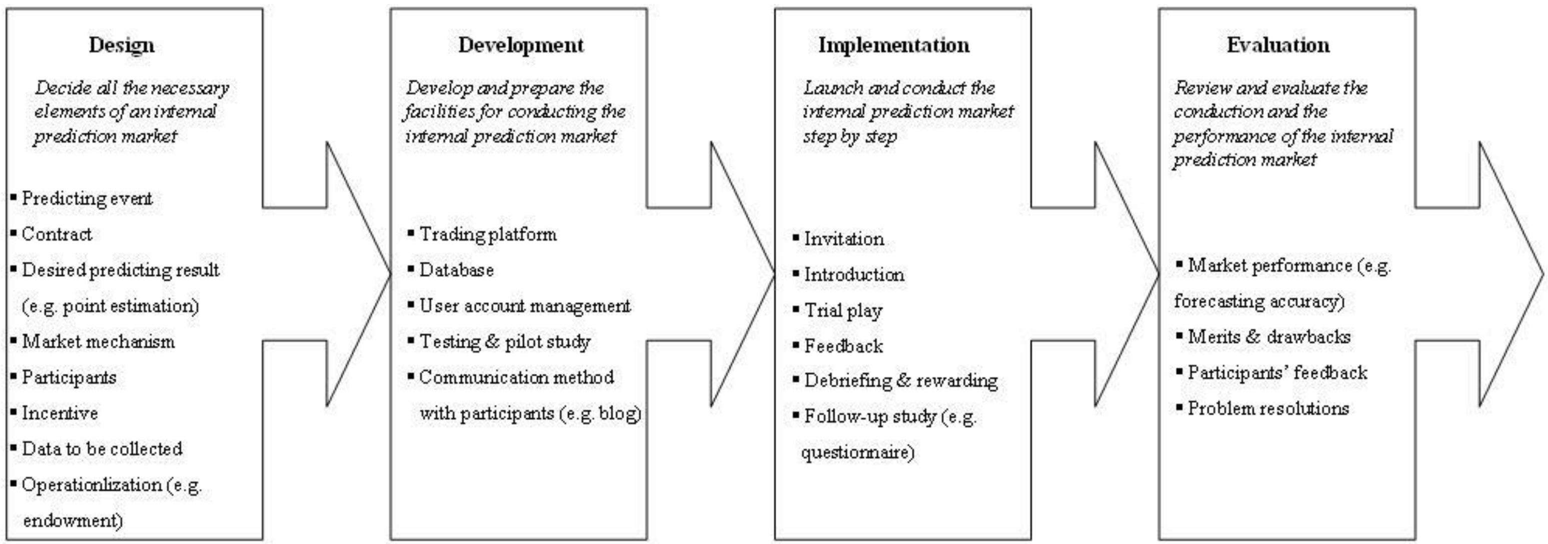

Figure 7.2a Conduction Procedures of an Internal Prediction Market

Figure 7.2b Conduction Cycle of an Internal Prediction Market

To gain an understanding of traders' activities, particularly, traders' dynamic interactions under different information transparency levels, we investigated traders' use of different information sources by a follow-up questionnaire survey after each laboratorial experimental market. However, this study did not allow us to instantly trace how a trader uses different information, particularly, price information for a trading decision. In addition, the survey results may reflect traders' subjective thoughts regarding how they incorporated different information sources in their trading decision rather than the actual behavior during the market. Consequently, the explanatory power of traders' use of information sources based on survey results is reduced.

With regard to managerial practice, we did not measure decision makers' perceptions about market performance. Although we explored their motivations for an internal prediction market, we did not evaluate the market performance based on their satisfaction. Similar to their different motivations, those decision makers, such as general managers, may hold different criteria of a market outcome. We measured market performance based on forecasting accuracy in this research. Nevertheless, in practice, it is in fact more important to assess if managers think that market performance is satisfactory according to their own criteria. A decision maker's evaluation of market performance fundamentally determines whether or not internal prediction markets will be conscientiously adopted inside a company.

7.5 FUTURE RESEARCH

With regard to the key variable of this research, namely information transparency, we focused on quote information. However, numerous types of price or non-price information can be shown on a web-based prediction market platform, such as the last five transactions of each contract and the dynamic ranking of traders. The presence or absence of a certain type of information is in fact another dimension of information transparency. To extend the research on information transparency in prediction markets, we suggest continuing with the aforementioned dimension.

As discussed in the limitations, we intended to capture traders' use of information sources in a prediction market. We are particularly interested in instantly observing the extent and consequences of the price information that captures a trader's attention. This may help us understand how information transparency affects traders' use of information sources that further influence the traders' learning. From a methodology perspective, an eye-tracking experiment is desired. Facilitated by eye-track equipment and software, all details of a subject's eye movement can be recorded, such as the watching sequence of objects and the duration of eye stay on a certain object. Duchowski (2007) introduced the possibility of tracking a subject's eye movements to allow researchers to follow along the path of the subject's attention. Thus, we may gain insight into what the subject found interesting, what drew his or her attention. We may even obtain a clue as to how that person perceived whatever scene he or she was viewing. Accordingly, in future research on trader's behavior in a web-based prediction market, an eye-tracking experiment can be adopted.

Human beings continuously learn during any form of interactions between them. During the field experiment in Wasu Taobao, we noticed that some employees in fact discussed the markets and future events via the company instant messenger and all the employees were allowed to see the chat. Thus, this online chatting platform became another learning channel for traders. Additionally, as employees are the primary traders in internal prediction markets, we can imagine that employees may talk about internal prediction markets offline during their workday. All these information exchanges outside the market are beyond the research scope in this dissertation. Nonetheless, it is interesting to consider these information sources in future study on trader's learning behavior in prediction markets. We may further investigate to what extent traders may reveal private information and learn from each other in these online or offline social interactions; how traders in turn incorporate learned information into their trading activities in a market; and if traders take advantage of these additional interactions to manipulate the market.

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APPENDIX

APPENDIX I QUESTIONNAIRE SURVEY FOR THE EXPLORATIVE CASE STUDY

Beste Relatiemanagers *** Bank!

Zoals jullie weten zijn jullie onderdeel van een uniek en belangrijk wetenschappelijk onderzoek, beter bekend bij jullie als de auctions. Wij willen graag wat meer achtergrond informatie verzamelen om de gegevens beter te kunnen interpreteren en daarvoor is deze korte enquete ter evaluatie van de eerste auction (verder genoemd de Maart auction) en de tweede auction (verder genoemd de Juni auction).

Het invullen van de vragenlijst duurt maximaal 10 minuten. Alle informatie die verzameld wordt middels deze vragenlijst wordt met de grootst mogelijke zorgvuldigheid en vertrouwelijkheid behandeld. De informatie wordt anoniem geanalyseerd en alle rapportage is op groepsniveau en zal uitsluitend gebruikt worden ter ondersteuning van de onderzoeksgegevens die al reeds uit de auctions naar voren zijn gekomen.

Alvast hartelijk bedankt!

PARTICIPATIE

1. Hoe actief heeft u deelgenomen aan de Maart auction?

☐ Extreem Inactief (0 keer ingelogdr)

☐ Inactief (1 - 5 keer ingelogd)

☐ Gemiddeld (6 – 10 keer ingelogd)

☐ Actief (11-20 keer ingelogd)

☐ Extreem Actief (meer dan 20 keer ingelogd)

2. Wat deed u meestal wanneer u inlogde in Maart?
Meerdere antwoorden mogelijk

- ☐ Niets
- ☐ Observeren van de bewegingen in de markt.
- ☐ Actief handelen in aandelen
- ☐ Bekijken van de status van mijn uitstaande orders (bijvoorbeeld toegewezen of niet)
- ☐ Anders ______________________________

3. Hoe actief heeft u deelgenomen aan de Juni auction?

- ☐ Extreem Inactief (0 keer ingelogdr)
- ☐ Inactief (1 - 5 keer ingelogd)
- ☐ Gemiddeld (6 – 10 keer ingelogd)
- ☐ Actief (11-20 keer ingelogd)
- ☐ Extreem Actief (meer dan 20 keer ingelogd)

4. Wat deed u meestal wanneer u inlogde in Juni?
Meerdere antwoorden mogelijk

- ☐ Niets
- ☐ Observeren van de bewegingen in de markt.
- ☐ Actief handelen in aandelen
- ☐ Bekijken van de status van mijn uitstaande orders (bijvoorbeeld toegewezen of niet)
- ☐ Anders ______________________________

5 Wanneer er nogmaals een auction gehouden zou worden, zou u dan mee willen doen? Meerdere antwoorden mogelijk

- ☐ Ja
- ☐ Nee

6. Waarom zou u weer willen meedoen?

____

7. Waarom zou u niet weer willen meedoen?

____

GEBRUIKTE INFORMATIEBRONNEN

De volgende vragen hebben betrekking op de MAART auction

8. Hoe vaak deed u een bod gebaseerd op uw eigen "gevoel" over wat een accurate voorspelling was?
   - ☐ Altijd
   - ☐ Vaak
   - ☐ Soms
   - ☐ Bijna nooit
   - ☐ Nooit

9. Hoe vaak nam u bij het doen van een bod het handelen van anderen in overweging? (bijvoorbeeld het hoogste bod, laagste verkoopprijs of laatste transacties)
   - ☐ Altijd
   - ☐ Vaak
   - ☐ Soms
   - ☐ Bijna nooit
   - ☐ Nooit

10. Hoe vaak nam u bij het doen van een bod de prijs van een aandeel in overweging?
    - ☐ Altijd
    - ☐ Vaak
    - ☐ Soms
    - ☐ Bijna nooit
    - ☐ Nooit

11. Hoe vaak nam u bij het doen van een bod de ***productie van *** van de afgelopen jaren in overweging?

- ☐ Altijd
- ☐ Vaak
- ☐ Soms
- ☐ Bijna nooit
- ☐ Nooit

12. Hoe vaak nam u bij het doen van een bod de ***productie van *** van de afgelopen maanden in overweging?

- ☐ Altijd
- ☐ Vaak
- ☐ Soms
- ☐ Bijna nooit
- ☐ Nooit

13. Welke informatie van buiten de auction nam u in overweging bij het doen van bod?

    ____

14. Maart auction Hoeveel tijd heeft u besteed aan het meedoen met de Maart auction, met uitzondering van de briefing die u heeft ontvangen op de relatiemanagersdag?

- ☐ Geen tijd
- ☐ Minder dan een uur
- ☐ Tussen een uur en een halve dag
- ☐ Een dag of meer

De volgende vragen hebben betrekking op de JUNI auction

15. Hoe vaak deed u een bod gebaseerd op uw eigen "gevoel" over wat een accurate voorspelling was?

- ☐ Altijd
- ☐ Vaak
- ☐ Soms
- ☐ Bijna nooit
- ☐ Nooit

16. Hoe vaak nam u bij het doen van een bod het handelen van anderen in overweging? (bijvoorbeeld het hoogste bod, laagste verkoopprijs of laatste transacties)

- ☐ Altijd
- ☐ Vaak
- ☐ Soms
- ☐ Bijna nooit
- ☐ Nooit

17. Hoe vaak nam u bij het doen van een bod de prijs van een aandeel in overweging?

- ☐ Altijd
- ☐ Vaak
- ☐ Soms
- ☐ Bijna nooit
- ☐ Nooit

18. Hoe vaak nam u bij het doen van een bod de ***productie van *** van de afgelopen jaren in overweging?

- ☐ Altijd
- ☐ Vaak
- ☐ Soms
- ☐ Bijna nooit
- ☐ Nooit

19. Hoe vaak nam u bij het doen van een bod de ***productie van *** van de afgelopen maanden in overweging?

- ☐ Altijd
- ☐ Vaak
- ☐ Soms
- ☐ Bijna nooit
- ☐ Nooit

20. Welke informatie van buiten de auction nam u in overweging bij het doen van bod?

____

21. Maart auction Hoeveel tijd heeft u besteed aan het meedoen met de Juni auction, met uitzondering van de briefing die u heeft ontvangen op de relatiemanagersdag?

- ☐ Geen tijd
- ☐ Minder dan een uur
- ☐ Tussen een uur en een halve dag
- ☐ Een dag of meer

VERKOOPVOORSPELLING

22 Hoeveel gepasseerde ***productie zou je gemiddeld als relatiemanager in 2007 uit het intermediaire kanaal kunnen halen, uitgaande van de gemiddelde hoofdsom in jouw district? Geef uw indicatie in miljoen EURO

____

23. Hoeveel geaccepteerde omzet zou je gemiddeld als relatiemanager in de periode *** 2007 (***campagne) uit het intermediaire kanaal kunnen halen, uitgaande van de gemiddelde hoofdsom in jouw district? (Geef uw indicatie in miljoenen euro's)

Geef uw indicatie in miljoen EURO

____

PERSOONLIJKE ACHTERGROND

24. Wat is uw naam? (uw gegevens zijn louter voor de Erasmus Universiteit en worden niet doorgegeven aan management of anderen binnen ***, volledige anonimiteit is gewaarborgd)

____

25. Wat is uw geslacht?

- ☐ Man
- ☐ Vrouw

26. In welke regio bent u werkzaam?

- ☐ Amsterdam
- ☐ Midden NL
- ☐ Rotterdam
- ☐ Zuid Holland
- ☐ Arnhem / Nijmegen
- ☐ IJsselland
- ☐ Noord Holland
- ☐ Oost Brabant
- ☐ Limburg
- ☐ Noord Nederland
- ☐ Oost Nederland
- ☐ W&M Brabant
- ☐ Zuid West NL

27. Hoe lang werkt u nu voor *** ***?

- ☐ Minder dan 1 jaar
- ☐ 1 – 3 jaar
- ☐ 3 – 5 jaar
- ☐ 5 – 10 jaar
- ☐ meer dan 10 jaar

28. Hoe lang werkt u nu in de *** markt?

☐ Minder dan 1 jaar

☐ 1 – 3 jaar

☐ 3 – 5 jaar

☐ 5 – 10 jaar

☐ meer dan 10 jaar

PERSOONLIJKHEID

		Sterk mee oneens				Sterk mee eens
28.1.	In onzekere tijden verwacht ik vaak het ergste.	☐	☐	☐	☐	☐
28.2.	Ik ontspan mij gemakkelijk.	☐	☐	☐	☐	☐
28.3.	Als bij mij iets verkeerd kán gaan, dan gáat het ook verkeerd.	☐	☐	☐	☐	☐
28.4.	Ik ben altijd optimistisch over mijn toekomst.	☐	☐	☐	☐	☐
28.5.	Ik geniet veel van mijn vrienden.	☐	☐	☐	☐	☐
28.6.	Ik vind het belangrijk om bezig te zijn.	☐	☐	☐	☐	☐
28.7.	Ik verwacht dat bijna nooit de dingen gaan zoals ik wil.	☐	☐	☐	☐	☐
28.8.	Ik ben niet gemakkelijk van mijn stuk te brengen.	☐	☐	☐	☐	☐
28.9.	Ik reken er bijna niet op dat mij goede dingen overkomen.	☐	☐	☐	☐	☐
28.10.	Over het algemeen verwacht ik dat mij meer goede dan slechte dingen overkomen.	☐	☐	☐	☐	☐

OPMERKINGEN

29. Ziet u het mogelijke nut van auctions voor ***. Indien u nog overige vragen, opmerkingen of klachten heeft over de auctions of deze vragenlijst, dan kunt u deze ook hieronder invullen.

APPENDIX II GENERAL INSTRUCTIONS OF THE EXPERIMENT

This experiment comprises of three rounds. Each round consists of a market and a questionnaire. The entire experiment is expected to accomplish within 60 minutes. The market allows you to trade contracts that represent the 2008 annual sales of a certain product category on TaoBao, a B2C and C2C online market in China.

Each player begins with 1,000 points play money and 10 shares of each contract in a market. There are five contracts in one single market. Only one of them represents the true annual sales of the product category in 2008. During the course of trading, you can buy or sell shares on any given contract. If you think that a contract corresponds with the true annual sales outcome, or you believe that the price of a contract is going to go up, buy shares of that contract from other players. If you think a contract does NOT correspond with the true sales result, or believe the price is going to go down, sell your shares of that contract to other players. Every market is open for 10 minutes. When a market is closed, you will no longer be able to trade.

On your table, you will find three piles of documents, labelled as Round 1, Round 2, and Round 3. They correspond with the rounds of experiments in sequence. Each pile of documents includes an instruction of the web-based trading system for that certain round, the monthly sales from January till June 2008 of the product in that certain round, a piece of private information - giving you the clue of the true annual sales, and a questionnaire. Please fill in the questionnaire when a market is closed.

Rewards:

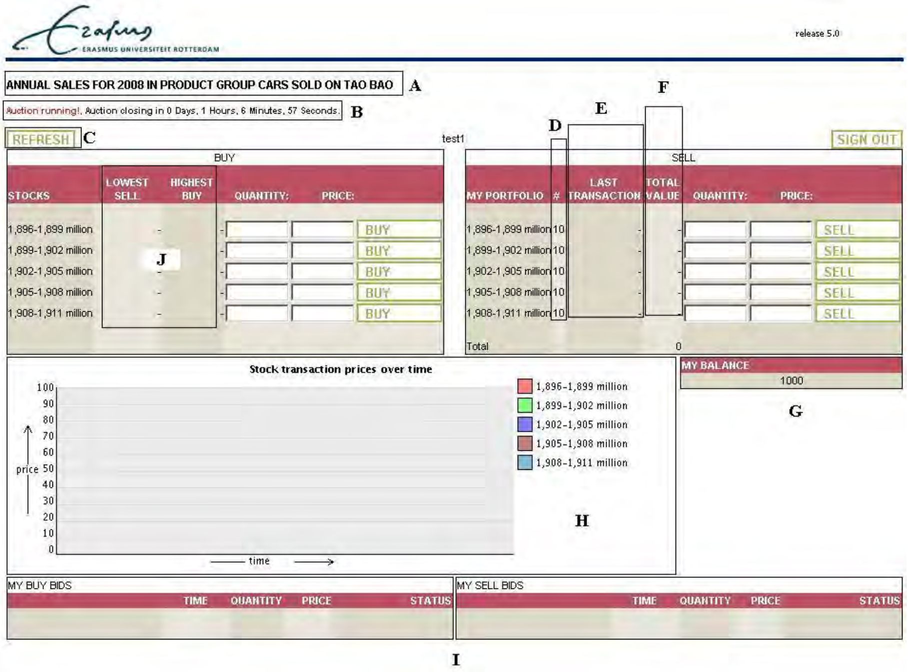
1. *Attendance reward:* every student who completes the entire experiment will be rewarded cash €10.00.
2. *Prediction based reward:* You can earn €0.50 euro per share exceeding the endowment (10 shares) of the contract which corresponds with the actual annual sales outcome of each market. The maximum number of shares you may earn = (total number of traders in your group – 1) * 10.
3. *Trading based reward:* when a market is closed, the person who has the most play money left in his or her funds will be rewarded €2.00. However, this person must have conducted trading in this market. Otherwise, this reward will be given to the person has the second most play money, and so on. In case that there is more than one person are eligible for this reward, the reward will be equally distributed among them.

Please note:

1. Do NOT communicate with any subject.
2. Please put on the headphone during the entire experiment.
3. If you have any problem with the web-based trading system, please come to the control room immediately and ask.
4. You can obtain the rewards only if you accomplish the entire experiment. The rewards will be distributed in the end of the entire experiment
5. When you finish the entire experiment, please leave all the documents on your table.

APPENDIX III AN EXAMPLE OF AN INFORMATION SET GIVEN TO A SUBJECT IN THE LABORATORY EXPERIMENTS

Prediction Market Platform Descriptions



A: Event being predicted in this market.

B: Status of the market.

C: Refresh so as to see all the updated information on the website. You may press the button "REFRESH" on the website frequently to see the most updated information. *Please do not press button "F5" on the keyboard to refresh the website, as it will lead you back to the login screen.*

D: Number of shares of each stock you possess.

E: Last transaction price of each stock. A transaction occurs when there is a buy order lower or equal to a sell order in terms of price.

F: Total value of each stock you possess = D * E.

G: The amount of play money available in your fund.

H: Line chart of all the transaction prices of each stock over the trading time.

I: Order status, including complete, running, or infeasible. When you find an order becomes infeasible, you cannot delete or change it, but submit a new order.

J: Lowest sell/Highest buy running order of each stock in the market. It will display as "quantity @ price" (e.g. 5@2). This information will update automatically, though with a bit delay. Therefore, we suggest you pressing "refresh" button for the most updated information.

<u>Please do not write on this page, as we will re-use it in the next experiment!</u>

Private Information

The event being predicted in this market is:

Sales of product category "Female Clothing" on TaoBao in 2008

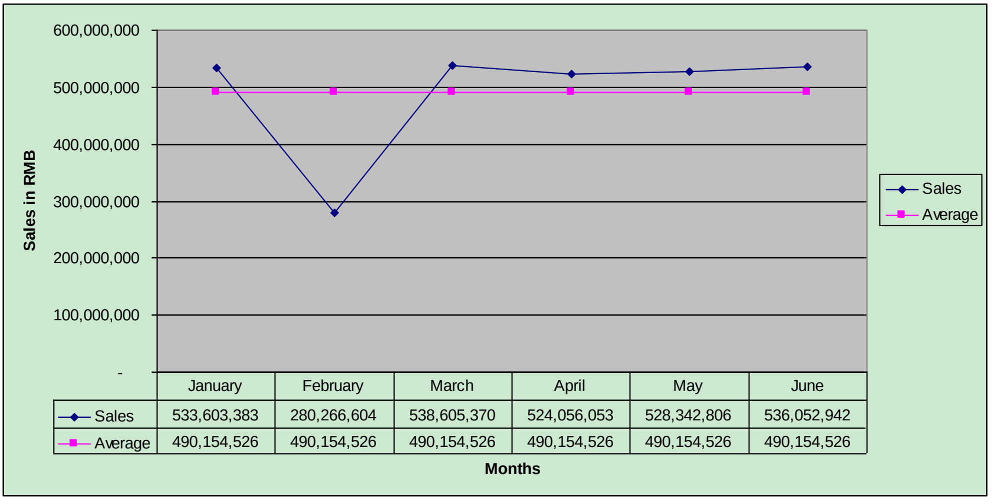
The inside information reveals that

> The actual sales of product category "Female Clothing" on TaoBao in 2008 does **NOT** lie in "***<u>7,911-7,914</u>*** million RMB".

<u>Please do not write on this page, as we will re-use it in the next experiment!</u>

Historical Sales Information

Sales of product category “**Female Clothing**” on TaoBao
from January to June in 2008



<u>Please do not write on this page, as we will re-use it in the next experiment!</u>

APPENDIX IV AN EXAMPLE OF A QUESTIONNAIRE AFTER EACH MARKET IN THE LABORATORY EXPERIMENTS

1. The historical sales information from January to June 2008 was important to my trading decisions.
   - ☐ Strongly agree
   - ☐ Agree
   - ☐ Neutral
   - ☐ Disagree
   - ☐ Strongly disagree

2. The private information regarding the annual sales in 2008 was important to my trading decisions.
   - ☐ Strongly agree
   - ☐ Agree
   - ☐ Neutral
   - ☐ Disagree
   - ☐ Strongly disagree

3. The line chart of transaction prices of each stock over the trading time period on the website was important to my trading decisions.
   - ☐ Strongly agree
   - ☐ Agree
   - ☐ Neutral
   - ☐ Disagree
   - ☐ Strongly disagree

4. The last transaction price of each stock on the website was important to my trading decisions.
   - ☐ Strongly agree
   - ☐ Agree
   - ☐ Neutral
   - ☐ Disagree
   - ☐ Strongly disagree

5. The "Lowest Sell" and "Highest Buy" of each stock on the website were important to my trading decisions.
   - ☐ Strongly agree
   - ☐ Agree
   - ☐ Neutral
   - ☐ Disagree
   - ☐ Strongly disagree

6. Please rank the following information sources from **1 (most important)** to **6 (least important)**
   - ☐ Historical sales information Jan-June 2008
   - ☐ Private information
   - ☐ Line chart of transaction prices on the website
   - ☐ Last transaction price of each stock on the website
   - ☐ Lowest sell / Highest buy of each stock on the website

GLOSSARY

A

Absolute accuracy: the accuracy of prediction markets that is evaluated against the actual outcome.

Adaptive learning: a theory states that economic agents initially may not know the exact information they need to predict the relevant outcomes. Nevertheless, the agents are willing and able to learn over time. As a result, the agents are able to keep updating their expectations based on the newly-received information.

Ask: a sell order made by a trader in a market.

B

Between-method triangulation: the use of multiple methods to examine the same dimension of a research problem.

Bid: a buy order made a by trader in a market.

C

Case study: an empirical inquiry that investigates a contemporary phenomenon within its real-life context, especially when the boundaries between a phenomenon and context are not clearly evident.

Collective wisdom: see the wisdom of crowds.

Collective intelligence: see the wisdom of crowds.

Continuous double auction (CDA): a market mechanism in which buyers submit bids and sellers submit asking prices and the mechanism executes a trade whenever the two sides of the market reach a mutually agreeable price. A CDA poses no risk for the market institution, as it only matches willing traders. However, a CDA may suffer from illiquidity in the form of huge bid-ask spreads or light trading.

Continuous double auction with market maker (CDAwMM): a market mechanism similar to CDA. This mechanism has a market maker, who is willing to accept a large number of buy and sell orders at particular prices. A CDAwMM has built-in liquidity, as the market maker itself is usually affiliated with the market institution. Nevertheless, the market maker is exposed to significant risk of large losses. As a result, the liquidity is at a cost.

Contract: a product traded in a prediction market.

D

Dynamic pari-mutuel market (DPM): a market mechanism that is a hybrid between a CDA and a PM. This DPM in turn solves the CDA's problem of illiquidity and allow for continuous information incorporation, which is not possible in a standard PM.

E

Efficient market hypothesis: in an efficient market, prices always "fully reflect" all available information.

Electronic market hypothesis (EMH): a hypothesis posits that advanced IT reduces coordination costs between suppliers and buyers and motivates the dominance of electronic market-based forms of economic activity. The EMH predicts that biased electronic markets will emerge as suppliers take advantage of IT to lock in buyers. However, unbiased electronic markets will gradually dominate. In unbiased electronic markets, all products and suppliers can be evaluated by buyers to make well-informed decisions and information is complete, accurate, and real time.

Engaged scholarship: an implication of a fundamental shift in how scholars define their relationships with the communities. This engagement refers to the relationship that involves negotiation and collaboration between researchers and practitioners in a learning community; such a community jointly produces knowledge that can both advance the scientific enterprise and enlighten a community of practitioners. This approach of engaged scholarship can address the widening gap between research and practice in management.

Experiment: a study in which an intervention is deliberately introduced to observe its effects.

F

Field experiment: an experiment employs a nonstandard subject pool with field context in the commodity, task, or information set that the subjects can use in the environment where the subjects naturally undertake these tasks and do not know that they are in an experiment.

I

Incentives: a monetary or non-monetary item that is given to motivate traders to trade and reveal information in a prediction market.

Index: a type of contract, in which the amount that the contract pays varies in a continuous way based on a number that rises for falls. This contract price represents the mean value that the market assigns to the outcome.

Information aggregation: a process that aggregates private information held by traders and disseminates this information in the market.

Information aggregation efficiency: the ability of the market to synthesize the traders' mean belief.

Information technology (IT): technological artifacts that enable electronic markets, such as Internet, network technologies, and communication technologies.

Information transparency: the degree of visibility and accessibility of information.

Information transparency hypothesis: a hypothesis posits that open sharing of information in electronic markets is beneficial to all traders.

Informed trader: a trader, who has a piece of information about the future event being predicted in a prediction market.

Internal prediction market: a prediction market that is used inside a company, only open for selected traders, who are usually employees.

Insider: see informed trader.

J

Judgmental forecasting method: a forecasting method that makes predictions by sourcing information from individuals. Examples: customer survey and expert opinions.

L

Laboratory experiment: an experiment that allows researchers to deliberately divorces a phenomenon from its context, and thus, focuses on only a few variables in a highly controlled environment.

M

Marginal trader: a trader who is relatively free of judgment bias, and thus, consistently buys and sells at prices very close to the equilibrium price, which reflects all the available information about the future events. These traders are usually more rational and can drive the efficiency of market prices in spite of large numbers of traders who display constantly suboptimal behavior.

Market transparency: the level of availability and accessibility of information about products and market prices.

Market scoring rules (MSR): a market mechanism that is developed based on scoring rules. A MSR can be conceptualized as a market provides a two-sided automated market maker that is always willing to accept a trade on any event at some price. A MSR allows for simultaneous predictions over many combinations of outcomes instead of requiring separate markets for each combination of possible outcomes.

Methodological pluralism: a position that favors a diversity of methods, theories, even philosophies, in scientific inquiry. It lies between the extremes of methodological monism and the anarchy of an "any-thing goes" attitude. The emergence of methodological pluralism in IS is mainly due to the gradual unfolding of the human, organizational, and social dimensions of this discipline.

O

Outsider: see uninformed trader..

P

Pari-mutuel market (PM): a market mechanism in which all of the money that is bet goes into a common pot and is then divided among the winners. A PM does not have the problem with liquidity or involve risks for loss, because traders can place a bet on any outcome at any time and no need for a market maker. Prices in this mechanism, however, do not reflect the continuously updated information, as traders do not place bets until either all information is revealed or the market is about to close.

Prediction market: designed and conducted for the primary purpose of aggregating information so that market prices forecast future events. In such markets, a group of traders trade in contracts whose payoff depends on unknown future events.

Prediction market mechanism: a market mechanism determines how buyers and sellers are matched in a prediction market.

Predictive accuracy: the most adopted measurement of prediction market performance. The smaller the discrepancy between a prediction and the actual outcome is, the more accurate is the prediction. Market predictive accuracy can be categorized in to absolute accuracy and relative accuracy.

Price transparency: the revelation of information about prices, such as current market prices, quotes, and historical transaction prices.

Public prediction market: a prediction market that gives free entry to any one.

R

Rational expectation theory: in the aggregate, the expected price is an unbiased predictor of the actual price. According to this theory, all available information to traders in a market is revealed by prices in the process of trading.

Relative accuracy: the accuracy of prediction markets that is evaluated against the prediction of competing forecasting methods.

S

Sequential triangulation: the use of multiple methods which requires a researcher to use the results of one method as the basis for a new study of the same concept with a different method. In turn, the methods are dependent.

Simultaneous triangulation: the use of multiple methods in the same study to measure the same phenomenon. By checking the consistency of the multiple evidences, the results of the study is considered more convincing.

Spread: a type of contract, in which, traders differentiate themselves by bidding on the cutoff that determines whether an event occurs. For example, either one team will win by at least a certain number of points or not in a football game. Combining with the setting that winners double their money while losers receive zero, the corresponding price indicates the market's expectation of the median outcome.

Statistical forecasting method: a forecasting method that makes predictions by discovering a pattern of historical data. Examples: time series models and structural models.

T

Thick market: a market with a large number of participants.

Thin market: a market with only a few participants.

Trader: a participant in a prediction market, who buys and sells contracts.

Trader's dynamic interaction: a trader's revision of buy or sell orders on contracts. It is not only the consequence of learning, but also the cause of another trader's revision.

Transparency strategy: a set of policies and decisions that a firm makes to disclose, conceal, bias, or distort market information.

Triangulation: the combination of methodologies in the study of the same phenomenon. Triangulation is a form of the pluralist methodology.

U

Uninformed trader: a trader, who does not have a piece of information about the future event being predicted in a prediction market.

W

Winner-take-all: a type of contract, in which the contract costs some amount of money and pays off only if a specific event occurs. The price on a winner-take-all market represents the market's expectation of the probability that an event will occur based on the assumption of neutral risk.

Wisdom of crowds: the aggregation of the dispersed information in groups.

Within-method triangulation: the use of multiple techniques within a given method to collect and interpret data, such as a survey questionnaire with different scales measuring the same "empirical uniP3."

SUMMARY

The increased complexity of the business environment, such as globalization of the market, faster introduction of new products, more interdependencies among firms and financial crises, has reduced the forecasting accuracy of conventional prediction methods based on historical data or experts. Over the past decade, some in the business world have come to believe that the best forecasts emerge from neither past behavior patterns nor far-removed experts who analyze markets, but rather crowds; the front-line employees who are working directly with new products and services and interacting daily with buyers, sellers and customers in the field, as they have the most relevant and updated information and knowledge required for forecasting.

A prediction market is an elegant and well-designed method for capturing the wisdom of crowds and predicting the outcome of a future event. Prediction markets can be powerful information-processing mechanisms that aggregate the views of multiple market traders to generate a prediction of the future. Its promising forecasting results have inspired much enthusiasm among both researchers and practitioners in recent years. The use of prediction markets for aggregating information about the future is based on the efficient market hypothesis and the rational expectations hypothesis. These theories suggest that prices in a market reflect all available information about the future, and therefore, prices imply the prediction of the future.

This dissertation entails two major research objectives. First, we aim to understand traders' behavior in a prediction market within a firm, as traders are often front-line employees and their behavior in a prediction market is dynamic and has a great effect on market performance. Second, this dissertation adopts the information-based view to investigate the effect of information transparency on prediction market performance. Accordingly, this dissertation answers the following two research questions: (1) *How do traders behave in an internal prediction market?*; and (2) *How does information transparency in an internal prediction market influence market performance*?

This dissertation adopts a pluralist methodology to investigate the research questions. The case study (Chapter 4) investigates the activity of and dynamic interactions between traders in an internal prediction market. The subsequent laboratory experiment (Chapter 5) examines the effect of price information transparency on market performance via traders' behavior. The field experiment (Chapter 6) further investigates different levels of price information transparency in an internal prediction market in a real business environment.

The results show that in a prediction market, the disclosure of different traders' buy and sell orders enhances dynamic interactions between traders, though the disclosure does not have an impact on traders' participation activity. However, the disclosure of all buy and sell orders will impede, rather than further improve, the traders' dynamic interactions in a market. Furthermore, increases in traders' participation activity and traders' dynamic interactions in a prediction market enhance the market's ability to aggregate dispersed information (i.e., information aggregation efficiency), and eventually, lead to more accurate prediction (i.e., market predictive accuracy).

This dissertation contributes to the academic literature on information transparency and prediction markets. With regard to information transparency, it extends current research by investigating its effect in a new type of market. Second, this work contributes to the research stream of transparency strategy by focusing on a particular information element (i.e., quote information) and its impacts (i.e., its influence on traders' behavior and market performance). This dissertation takes an information-based view to study prediction markets and highlights the importance of information transparency in their design. This research distinguishes between information aggregation efficiency and market predictive accuracy for the analysis of prediction market performance by defining and developing a measurement of information aggregation efficiency. It examines traders' activities in a real business environment to enhance our understanding of traders' behavior in an internal prediction market and its influence on market performance, improving the design of internal prediction markets. Furthermore, our empirical study in a new, dynamic and highly uncertain business environment demonstrates the considerable potential of prediction markets in managerial decision-making.

NEDERLANDSE SAMENVATTING (DUTCH SUMMARY)

De toegenomen complexiteit van bedrijfsomgevingen, zoals de globalisering van de markt, snellere introductie van nieuwe producten, meer onderlinge afhankelijkheid tussen bedrijven en de financiële crisis, heeft de nauwkeurigheid van conventionele voorspellingsmethoden op basis van historische gegevens of deskundigen verminderd.

De afgelopen tien jaar, zijn sommigen in de zakelijke wereld ervan overtuigd geraakt dat de beste voorspellingen niet gegenereerd worden via gedragspatronen uit het verleden noch middels experts die markten van ver af analyseren, maar via de massa; de eerstelijns medewerkers die werken met nieuwe producten en diensten en de dagelijkse interacteren met kopers, verkopers en klanten in het werkveld, omdat ze over de meest relevante en actuele informatie en kennis beschikken die nodig is voor het voorspellen.

Een voorspellingsmarkt is een elegant en goed ontworpen methode voor het vastleggen van de wijsheid van de massa en het voorspellen van de uitkomst van een toekomstige gebeurtenis. Voorspellingsmarkten kunnen krachtige informatieverwerkende mechanismen zijn die de meningen van meerdere markthandelaren aggregeren om een voorspelling van de toekomst te genereren. De veelbelovende voorspellingsresultaten hebben in de afgelopen jaren tot veel enthousiasme geleid bij zowel onderzoekers als practici. Het gebruik van voorspellingsmarkten voor het aggregeren van informatie over de toekomst is gebaseerd op de efficiënte markt hypothese en de rationele verwachtingen hypothese. Deze theorieën stellen dat de prijzen in een markt alle beschikbare informatie over de toekomst weerspiegelen en dat daarom de prijzen, het voorspellen van de toekomst, impliceren.

Dit proefschrift omvat twee belangrijke onderzoeksdoelstellingen. Ten eerste is het doel om het gedrag van handelaren in een voorspellingsmarkt binnen een bedrijf te begrijpen, aangezien de handelaren vaak eerstelijns werknemers zijn en hun gedrag in een voorspellingsmarkt dynamisch is en een groot effect heeft op de prestaties van de markt. Ten tweede, neemt dit proefschrift een op informatie-gebaseerd perspectief om het effect van transparantie van informatie op de prestatie van de voorspellingsmarkt te onderzoeken. Derhalve beantwoordt dit proefschrift de volgende twee onderzoeksvragen: *(1) Hoe gedragen handelaren zich in een interne voorspellingsmarkt?* en *(2) Hoe beïnvloedt transparantie van informatie de marktprestatie in een interne voorspellingsmarkt?*

Dit proefschrift volgt een pluralistische methodologie om de onderzoeksvragen te bestuderen. De case studie (Hoofdstuk 4) onderzoekt de activiteit van en de dynamische interacties tussen handelaren in een interne voorspellingsmarkt. Het daaropvolgende laboratoriumexperiment (Hoofdstuk 5) onderzoekt het effect van prijsinformatie transparantie op marktprestatie via het gedrag van handelaren. Het veldexperiment (Hoofdstuk 6) onderzoekt nader de verschillende niveaus van prijsinformatie transparantie in een interne voorspellingsmarkt in een daadwerkelijke bedrijfsomgeving.

De resultaten tonen aan dat in een voorspellingsmarkt, de openbaarmaking van de koop- en verkooporders van verschillende handelaren de dynamische interacties tussen handelaren verbetert, alhoewel de openbaarmaking geen invloed heeft op de participatie activiteit van handelaren. Echter, de openbaarmaking van de koop- en verkooporders, belemmert eerder dan dat het de dynamische interacties van handelaren in een markt verder verbetert. Bovendien verbeteren toenames in de participatie activiteit en de dynamische interacties van handelaren het vermogen van de markt om verspreide informatie te aggregeren (i.e. informatie aggregatie efficiëntie) en leiden uiteindelijk tot een meer nauwkeurige voorspelling (i.e. de marktvoorspellende nauwkeurigheid).

Dit proefschrift draagt bij aan de academische literatuur over informatie transparantie en voorspellingsmarkten. Ten eerste, met betrekking tot de transparantie van informatie, verlegt het de grenzen van huidige studies over transparantie van informatie door deze effecten te onderzoeken in een nieuw type markt. Ten tweede, draagt dit werk bij aan de onderzoekstroming van transparantie strategie door zich te richten op een specifiek informatie-element (i.e. quote informatie) en de impact daarvan (i.e. de invloed daarvan op het gedrag van handelaren en de marktprestaties). Met betrekking tot de voorspellingsmarkten, neemt dit proefschrift ten eerste een op informatie gebaseerd perspectief om te voorspellingsmarkten te bestuderen en benadrukt het werk het belang van transparantie van de informatie voor het ontwerp van voorspellingsmarkten. Ten tweede, maakt dit onderzoek onderscheid tussen informatie aggregatie efficiëntie en markt voorspellende nauwkeurigheid voor de analyse van prestatie van de voorspellingsmarkt door het definiëren en ontwikkelen van een maatstaf voor informatie aggregatie efficiëntie. Ten derde, bestudeert dit onderzoek de activiteiten van handelaren in een daadwerkelijke bedrijfsomgeving om het begrip te vergroten van het gedrag van handelaren in een interne voorspellingsmarkt en de invloed hiervan op de prestatie van de markt, daarmee het ontwerp van de interne voorspellingsmarkten verbeterend. Bovendien, blijkt uit onze empirische studie in een nieuwe, dynamische en uiterst onzekere bedrijfsomgeving het aanzienlijk potentieel van voorspellingsmarkten voor de besluitvorming van managers.

跋

與國而貿經年積弊日重往一家一說卜其市而不得乃有卜市論出飽學之士論之商賈用之從上賢而多譽其實乃眾其華乃智集眾智以問未來蓋眾用眾有其知在民

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ABOUT THE AUTHOR

ShengYun (Annie) Yang was born in 1981 in Shanghai, China, and came to the Netherlands to pursue her higher education. Between 2005 and 2006, she studied at Rotterdam School of Management and was awarded the degree of Master of Science in Business Administration, Business Information Management (BIM). While working towards her degree, Prof. Eric van Heck introduced a prediction market in the Information Strategy course. Annie was convinced that prediction markets would become a promising forecasting tool in business in the near future. Therefore, after completing the Master of Science, she applied for the PhD program to research prediction markets and had the privilege of studying under Prof. Eric van Heck.

Before joining the academia, she was actively involved in the business world, including the fashion and automotive industries, for four years. Her experience in the business world enabled her to independently manage the empirical studies during her PhD. Particularly, her solid professional connections with the e-commerce sector in China helped her conduct successful laboratory and field studies on prediction markets in an innovate industry.

Annie has many research interests in addition to her research on prediction markets. Since completing her master's thesis, she has maintained her interest in e-commerce in China. In 2009, she published her first academic paper based on her thesis research. In 2010, she developed her work into a teaching case with Prof. Mark Greeven, Prof. Eric van Heck, Prof. Barbara Krug and the case specialist Tao Yue and published it through The Case Centre. In March 2012, a business case based on this work was also published on the Financial Times.

In 2011, with the ambition to fill in the gap between research and practices, she established her own business information consultancy firm. Her firm helps companies to leverage resource planning, raise management efficiency and increase brand awareness in their target markets. In tandem with those initiatives, she has been actively working on a project to introduce prediction markets to more people and business sectors in the near future.

Since 2013, she has been involved in research projects in China. In December 2013, she was invited to present her explorative study on advanced metering infrastructure at the Shanghai Symposium on Remote Sensing and Social Development. Later, she was invited to become a member of the China Association for Science and Technology. Since the beginning of 2014, she has been invited to join several research centers of national-level enterprise and postdoctoral workstations in Zhejiang, China.

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INFORMATION AGGREGATION EFFICIENCY OF PREDICTION MARKETS

The increased complexity of the business environment, such as globalization of the market, faster introduction of new products, more interdependencies among firms and financial crises, has reduced the forecasting accuracy of conventional prediction methods based on historical data or experts. How can we predict the future? Where can we find information about the future?

Over the past decade, some in the business world have come to believe that the best forecasts emerge from neither past behavior patterns nor far-removed experts who analyze markets, but rather crowds; the front-line employees who are working directly with new products and services and interacting daily with buyers, sellers and customers in the field, as they have the most relevant and updated information and knowledge required for forecasting. A prediction market, an elegant and well-designed method for capturing the wisdom of crowds and predicting the outcome of a future event, has been, therefore, introduced. Its promising forecasting results have inspired much enthusiasm among both researchers and practitioners in recent years.

This dissertation adopts the information-based view to investigate the effect of information transparency on traders' behavior and prediction market performance. The research consists of three empirical studies. The case study investigates the activity of and dynamic interactions between traders in an internal prediction market. The subsequent laboratory experiment examines the effect of price information transparency on market performance via traders' behavior. The final field experiment further investigates different levels of price information transparency in an internal prediction market in a real business environment. The dissertation distinguishes clearly between information aggregation efficiency and market predictive accuracy for the analysis of prediction market performance by defining and developing a measurement of information aggregation efficiency. This research, as a whole, contributes to the academic literature on information transparency and prediction markets, and also demonstrates the considerable potential of prediction markets in managerial decision-making.

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